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Polarization or Upgrading?

The Effect of Automation on Occupational Change in Europe

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Introduction

In the 21st century, technological progress is constantly changing the world we are living in. Most of all, digital technology seems to have a profound impact on our daily lives: We read newspapers on smartphones, we share information on social media and, not least, a significant part of us is spending many hours every day working in front of a computer. All these aspects of our lives would look very different without digital technology.
Usually, technological innovations promise an improvement of some sort: We can carry out our tasks with less effort than before, or we are able to perform entirely new tasks for the first time. Therefore, one could assume that technological innovations in general improve our lives. Without a doubt, most innovations are meant to do so. However, some strong concerns have been raised recently about the effects of technological progress on labor markets. The main argument is that, as computers become more powerful, machines can replace human labor in a much larger scale than ever before, thus leading to drastic changes on labor markets.

Already in the 19th century, Karl Marx feared that machines were going to replace human labor in the long run and that there would be widespread unemployment among the working classes (Marx 2014). With the continuous development of technology, many others followed in Marx' footsteps and warned of a dystopian future due to a large-scale replacement of human labor by machines. Although the predicted effects could not be observed during the whole 20th century, the discussion regained popular attention in the beginning of the 21st century. The cause for this debate to heat up again clearly lies in the assumption that recent technological progress is somehow different than during Marx' times: In the past, there might have been some replacement of human labor by machines, mainly in industrial production where machines could easily emulate certain manual tasks. But at the same time, innovative technologies have always created enough new jobs to compensate for the ones that disappeared. Obviously, this balance of job-loss and job-creation depends heavily on the abilities of machines. It seems safe to assume that human labor is generally employed in occupations consisting of tasks that machines cannot emulate in a satisfying manner (also considering the costs of buying the machine). With limited technological possibilities, there were always enough tasks that only humans could do. But with recent developments in artificial intelligence and complex algorithms, machines become more powerful than ever before. Now they can not only emulate simple manual, but also complex cognitive tasks. Therefore, many occupations, that were safe until recently, could now be at risk of being replaced by machines (Brynjolfsson and McAfee 2012, 2016).

Fortunately, this has not (yet) led to widespread unemployment until today. Apparently, there are still enough tasks that humans are better suited for than machines. Nevertheless, technological progress is still regarded as the main driver of occupational change: Some occupations are slowly disappearing due to automation, while others benefit from the use of technology and thus become more numerous (Autor 2015; Berman, Bound, and Machin 1998). But which occupations are we talking about? In the academic literature, two theories dominate the discourse. The classic theory suggests that mainly occupations with low skill requirements can be replaced by machines, because they consist of tasks that are not too difficult to emulate. At the same time, demand for more skilled labor rises, since machines allow for higher productivity, but still require some creative inputs or control from highly skilled workers. This has become known as the theory of skill-biased technological change (SBTC). Thus, following this theory, we might expect that technological progress is leading to an occupational upgrading of the whole labor market, where low skilled occupations slowly disappear, and the share of high skilled occupations rises over time (Levy and Murnane 1996).

Another approach has been developed more recently, and instantly gained much attention: the theory of routine-biased technological change (RBTC). Other than on skill requirements, it focuses on the specific tasks of different occupations. The basic assumption is that machines can more easily emulate routine tasks than others, regardless of their complexity or skill requirements. Contrary to what one might expect, occupations with a high share of routine tasks are not mostly found at the bottom of the skill distribution, but in its middle (e.g. craft workers or office clerks). Therefore, these jobs should be most susceptible to automation, while numbers of occupations with low or high skill requirements remain relatively stable or even rise. Thus, according to RBTC, technological progress should be leading to a polarization of labor markets (Autor, Katz, and Kearney 2006).

The consequences of occupational change are obviously far-reaching: Since skill requirements are usually seen as key determinants of an occupation's wage, the income structure of societies might be rearranged drastically depending on the pattern of occupational change (upgrading or polarization) (Goos and Manning 2007). In a case of general occupational upgrading, for example, many participants of the labor market are expected to move to better paid jobs over time. Lower income occupations are slowly disappearing, and new well-paid jobs are created. Thus, a rising share of the labor market will be employed in occupations with high salaries, while low incomes become fewer over time. Assuming that incomes within occupations remain constant, this would not only lead to higher overall levels of income, but to a more compressed income distribution.

In a situation of labor market polarization however, this is not the case: If middle-income jobs disappear, a gap between lower- and upper-income earners develops. This is usually seen as problematic in at least two ways: First, large groups of middle-income earners might be facing serious risks of downward mobility if machines take over their jobs and they don't succeed in finding a better one (Autor and Dorn 2013). This is certainly unwanted by at least the directly affected people. Second, the risk of social tensions might increase if middle-income jobs disappear and labor markets become dominated by two polarized groups. Even more than inequality, polarization is often seen as a cause for social conflict due to its clear display of opposing interests. In situations of high inequality there might still be a continuous distribution of wealth or income, thus making it hard for people to form groups of interest. But in a situation of polarization this is not the case: Here, there are only two groups and it is usually quite clear which one a person belongs to, since there is not much common ground between them. Thus, polarized groups are quite likely to develop an antagonistic character, especially if the polarization is based on something as fundamental as income or wealth (Esteban and Ray 1994).

Evidence in support of SBTC or RBTC has both been observed in many different empirical studies. They all share the insight that occupations with high skill requirements and high incomes have increased their share on labor markets in Europe and the USA over the last decades. But if we look at the development of middle- and low-skilled occupations, results vary significantly, depending on sample selection and methods of choice. First, there seems to be a change over time from upgrading to polarization: In the second half of the 20th century, general upgrading seemed to be the normal case for many countries. Then later, in the 21st century, the same countries sometimes moved on to a pattern of polarization (Acemoglu and Autor 2011; Wright and Dwyer 2003). However, not all of them did do so. Some countries continue to show a clear pattern of general occupational upgrading, neither with a significant increase in low-skilled occupations nor with an alarming erosion of the middle class. Among the countries that are often found to display a clear pattern of polarization are the USA and the UK (Autor et al. 2006; Goos and Manning 2003, 2007), while Scandinavian countries are regularly mentioned as examples for occupational upgrading without polarization (Fernández-Macías 2012; Oesch 2013). However, different authors don't always agree on the pattern of occupational change that they find in a country. Different methodical approaches and case selections seem to lead to different conclusions. Probably also for this reason, a consensus about the general trends of occupational change in Europe does not exist yet. Some recent authors state a trend towards polarization with much conviction (Goos, Manning, and Salomons 2009, 2014), while others find both patterns simultaneously (Fernández-Macías 2012), or even a general trend towards occupational upgrading (Oesch

2013). Therefore, the goal of this thesis is to explain the mixed evidence concerning occupational change in Europe.

To begin searching for an answer, I review again in chapter 1 the most important theoretical concepts that try to explain how technology shapes occupational change. These are the theories of SBTC and RBTC. Both of these theories explain what makes certain occupations more susceptible to automation than others. These theories' implications regarding upgrading or polarization are also discussed in more detail in this chapter.

Next, I present a selection of influential empirical studies about the topic in chapter 2. Some of the most regarded papers are based on data about the USA, why I don't want to leave them out, but much of the presented evidence is based on European countries. As already mentioned, there is evidence for upgrading *and* polarization effects, depending on case selection and methods of analysis. Therefore, I am going to compare the studies with regard to these characteristics, hoping that this might give us a first hint why different authors find different patterns of occupational change in Europe. If, for example, different methods systematically produce different results, I would have to consider this in my own analysis.

Starting with chapter 3, I present findings from my own analysis. By using a large dataset of the European Labor Force survey (ELFS), I examine the patterns of occupational change in 23 European countries over 17 years from 1998 until 2015. In chapter 3, I describe this dataset and the change it displays for different occupational groups over time. Most importantly, I describe which groups increase or decrease their employment share over time and which specific occupations are growing or disappearing fastest.

In chapters 4 and 5, I examine whether national labor markets display patterns of upgrading or polarization. To do so however, I must first create a ranking of occupations. In the literature, occupations are most often ranked by their skill requirements, but these are not always measured the same way. Some authors measure them based on educational attainments, others according to occupations' mean or median income. I decide to use both, since different measurements might lead to different conclusions. Thus, chapter 4 describes the patterns of occupational change regarding the educational structure, and chapter 5 does the same regarding the wage structure.

Since chapters 4 and 5 systematically show different results, I examine the data more closely in chapter 6. Obviously, some occupations must be ranked differently in the educational structure than in the wage structure, and vice versa. Only this can cause the observed discrepancy in patterns of occupational change. By analyzing the composition of growth or decline across the educational and the wage structure, I assess which occupations are responsible for this phenomenon. Based on these findings, I then argue that patterns of occupational change must always be analyzed separately for the educational and the wage structure. Following this, I am going to examine whether patterns of occupational change in these two structures can really be explained by how easily certain occupations can be emulated by machines, as proposed by SBTC or RBTC. As it turns out however, none of the proposed measures of susceptibility to automation are powerful enough to explain the observed patterns of occupational change all by themselves. Thus, I conclude that there must be other relevant factors than technical feasibility that define occupational change.

Based on this insight, I present several other potential determinants of occupational change in chapter 7. First, I introduce a new theoretical framework, in order to properly include the alternative effects into theory. I argue that occupational change is not only defined by how easily certain tasks are automated, but also by the potential benefits of doing so. As examples, I discuss the benefits of saving wages and of potential productivity gains. Further, I argue that the human preference for interpersonal contact might prevent automation of certain jobs. Lastly, I add to the list of potential influences the effect of offshoring which is frequently discussed in debates on occupational change.

Even though a combination of these effects might be able to explain general trends in occupational change, they are unable to explain the observed differences between countries. Therefore, chapter 8 deals with this issue. First, I show how patterns of occupational change depend on the original composition of labor markets. Next, I examine how national institutions affect the wage structure of labor markets and thus the cost-benefit analysis of employers who are thinking about automation of jobs. Lastly, I also show how growth of occupations at the top of the employment structure is depending on supply of highly educated workers.

Finally, I briefly want to examine the connection between patterns of occupational change and unemployment in chapter 9. Different authors claim that upgrading of labor markets drastically reduces the number of jobs which are available to workers with low education. In a situation of labor market polarization however, many jobs with low educational requirements are available, and even more are newly created. Thus, unemployment is expected to be higher in upgrading labor markets than in polarizing ones. Therefore, I want to test whether this holds true for the sample used in this thesis.

1. Competing Theories

Since the beginning of industrialization, people have been worried about the increasing use of machines and its consequences for human labor. In the 19th century, Karl Marx was one of the first authors to analyze the developments of his time systematically. He concludes that automation would, on one hand, transform human labor from skilled artisans into mere mechanical parts of machines, causing general downgrading of skills. On the other hand, he claims that machines will replace human labor increasingly and therefore cause massive unemployment among the working classes (Adler 1990; Marx 2014).

Marx might have been right to draw these conclusions, based on the empirical evidence in his time. However, labor markets developed quite differently in the meantime. According to academic consensus, automation has neither led to widespread unemployment nor a downgrading of skills. In fact, quite the opposite took place: Employment rates and demand for highly skilled labor have risen higher than ever before (Autor 2015). And, as most authors conclude, technology was responsible for this. Of course, other effects such as offshoring or the economic cycle, might offset the effect of technology in short timeframes. But in the long run, technology is generally assumed to be responsible for the most drastic changes in the occupational structure (Berman et al. 1998). For instance, one of the most drastic changes in recent history happened in the agricultural sector: Employment in agriculture decreased from 41% of the labor market to less than 2% in the USA during the 20th century (Autor 2014). Since production increased at the same time, automation of agricultural work is likely to be the main driver of this development (Dimitri, Effland, and Conklin 2005). But why did technology have such an impact for occupations in this sector and less so in others? To answer this question, I am going to discuss the most important contemporary theories about technology and occupational change in this chapter. All present theories try to explain why technology is a main cause for recent occupational change and how different occupations are affected in different ways by technological progress.

First, I am going to present the theory of skill-biased technological change (SBTC) in more detail. This approach has been the standard explanation of occupational change until quite recently, when it was challenged by a new theory which I present in the second section of this chapter: routine-biased technological change (RBTC). Those two approaches are certainly the most influential and most widely discussed theories about occupational change.

Skill-Biased Technological Change (SBTC)

I already mentioned Marx who argued that technology would replace skilled workers and lead to a general downgrading of skills. This was probably true during his times, when skilled artisans were replaced by machines and large scale industrial production fostered demand for cheap, unskilled labor (Goldin and Katz 1998). However, more recent computer technology seems to have turned this effect into its opposite: As technology became more complex, using it became increasingly demanding. This is easy to see if we compare classical assembly-line machinery with modern computers. In the assembly-line, workers typically had to repeat the same simple mechanical movements, because the machine was not capable of dealing with any other inputs. But with modern computers, the potential combinations of inputs are limitless (as are the outputs) and therefore, using a computer generally requires more skills than being part of an assembly-line. Even simply understanding how computers can be used is usually much more demanding than understanding what an assembly-line does. In addition, people working with computers are often required to decide about inputs themselves. To do so, they need abstract analytical skills "such as problem-solving or creative thinking" (Oesch 2013:14). Examples are graphic designers, software engineers, or all kinds of managers. They use computers, but their skills cannot be emulated by machines (yet). In the opposite: Their skills are complementary to what machines can do and are therefore essential for any production in their respective sector. Moreover, machines increase the potential output of workers who own these skills, making them more efficient and therefore more profitable. Thus, many authors expect recent technology to increase demand for highly skilled labor (Autor, Katz, and Krueger 1998; Bell 1973; Levy and Murnane 1996; Spitz-Oener 2006).

On the other hand, recent technological change is also expected to decrease demand for lowly skilled labor according to SBTC. The reason is that machines are generally built to replace human labor, but they are better capable of emulating some tasks than others. And as supporters of the SBTC-approach claim, machines are more capable of emulating tasks typically found in low skilled occupations than those found in high skilled occupations. For example, they can more easily emulate the work of assembly-line workers and farmers than the work of professors and managers. If we want to know why, we must look at the characteristics of different tasks. As already mentioned, occupations requiring high skills typically include a fair amount of abstract analytical tasks, which are difficult to emulate because they require creativity or complex deliberation. Easier to emulate however are tasks that can be fully described by a clearly defined set of rules. Whether this is sawing boards in 2 meters length or watering each plant on a field with a certain amount of fertilizer, these rules can be followed without much creative thinking. For this reason, it is possible to define these rules explicitly and build machines that can follow them. And as soon as a machine can perform the same task as a human worker, it seems only a matter of time until it starts replacing human labor in this domain. Now if we look at the tasks typically found in low skilled occupations, we find that they often have a mechanical and repetitive character. In consequence, they can be easily described by rules and therefore fulfilled by machines. Thus, machines are more capable of replacing low skilled labor than replacing high skilled labor, which leads to a relative decrease in demand of low skilled labor (Acemoglu 2002; Fernández-Macías and Hurley 2017).

To sum it up, SBTC claims that technological change increases demand for high skilled labor and decreases demand for low skilled labor. Accordingly, the share of high skilled labor is expected to rise, while low skilled labor should become less prevalent. In the literature, this is called occupational upgrading.

Routine-Biased Technological Change (RBTC)

The theory of skill-biased technical change was very prominent in the 1990s and continues to be one of the main approaches to explain occupational change. However, in the early 2000s, another idea started to question essential assumptions of SBTC: New authors such as Levy & Murnane (1996) or Autor, Levy and Murnane (2003) raised the question whether automation of labor really affects low skilled occupations the most. Even though they agree that occupations with a mechanical and repetitive (routine) character are most affected by automation, they disagree about which occupations are in fact possessing these qualities.
Their main argument is that skill requirements of occupations are not as closely related to their respective task content as claimed by SBTC: Some occupations with low skill requirements might have a low degree of routine work, which makes them hard to emulate, and some occupations with high skill requirements might have a high degree of routine work, which makes them easier to emulate. Thus, according to these authors, skill requirements are not good predictors of whether occupations can be automated or not. Instead, they claim that we must examine the routine content of occupations directly, since this is what really makes occupations susceptible to automation (Acemoglu and Autor 2011, 2012). Based on this insight, the authors of RBTC categorize occupations into different groups, depending on the nature of tasks that they consist of. In the pioneering work by Autor, Levy and Murnane (2003), three different categories are described.

First, there are occupations which consist mainly of routine tasks. They are the ones that are clearly most susceptible to automation, independently of whether these tasks are manual or cognitive. By definition, every kind of routine task can be translated into a set of explicit rules which can be followed by machines. Therefore, this category includes harvesting workers or assembly line workers, but also higher skilled occupations such as bank tellers or bookkeepers. Clearly, the tasks of some occupations in this group might be more complex than the tasks of others. However, this is not what matters, since even complex tasks can sometimes easily be codified. Complex mathematical calculations, for example, require many years of education, but are always to solve by the same strategy. Therefore, electronic calculators have replaced human computers long ago.

Second, Autor, Levy and Murnane describe occupations which consist mainly of analytic and interactive non-routine tasks. Among them are scientists, doctors, and lawyers, but also managers and negotiators. These tasks are very difficult to emulate because they require creative or analytical skills as well as the capability to interact with people, which computers currently don't possess yet. Instead, these occupations often benefit from strong complementary effects, since their work is made more efficient by computers. Thus, the authors expect this group of occupations to grow with technological progress.

Third, they find a group of occupations which mainly consist of manual non-routine tasks. Janitors, cleaners or truck drivers are mentioned as examples for this group. They all have in common that they neither require the analytical or creative skills needed for abstract tasks, nor are they definable enough by a strict set of rules to be called routine. Usually, these jobs can be done with very little training or education, only basic communication skills and hand-eye coordination is needed. But nevertheless, they cannot easily be replaced by machines because interpersonal communication and body control are clearly non-routine activities: Every part of a conversation is - in a sense - a unique situation with its own rules. And even cleaners or drivers, who don't need to communicate much except for taking orders, must adapt constantly to different environments which makes it hard to find universally valid rules for their jobs. Humans seem to master these challenges almost instinctively without much consideration, but for machines this is much more difficult. Manual non-routine tasks are therefore not easily emulated by machines. Other than analytic and interactive non-routine occupations however, manual non-routine occupations don't benefit from complementary effects either, since computers don't make their work much more efficient. Thus, the labor market share of this group is expected to remain relatively constant.

If we look at the skill requirements of these three groups, we find with little surprise that occupations containing analytic and interactive non-routine tasks are typically the ones with the highest skill requirements. They are expected to increase their numbers for the same reasons as given before. On the other side, manual non-routine occupations usually require the least skills of all. According to SBTC, this group would be bound to shrink because of a decrease in demand for unskilled labor. But since machines cannot easily emulate manual non-routine tasks, this is not likely to happen according to RBTC. The only group that is bound to shrink according to this approach is the group of routine occupations. And these are now found in the middle of the skill distribution, not at the bottom, as claimed by SBTC. Thus, the authors of RBTC conclude that the important distinction is not between levels of skills, but between levels of routine (Acemoglu and Autor 2011). Therefore, this effect is called routine-biased technological change (RBTC) (Goos et al. 2014).

The prevalence of routine occupations in the middle of the skill spectrum has important implications for the structure of the whole labor market. If occupations in the extremes of the spectrum become more prevalent and numbers of jobs requiring medium skills are decreasing, we find ourselves in a situation of labor market polarization. Instead of a continuous distribution of skills in the labor market, two distinct groups with opposed characteristics emerge. This is of special importance, because levels of skill are closely connected to levels of income in general (Liu and Grusky 2013). Therefore, if the labor market becomes polarized with respect to skills, it is very likely that there will also be a polarization regarding incomes (Autor et al. 2006). Some of the people working in routine occupations might make the step up and get a high skilled job. But many of them will only have the option to settle for a job with low skill requirements, thus facing downward mobility (Autor and Dorn 2013). According to RBTC, technological change is thus likely to increase income inequality (Autor et al. 2006).

If we compare SBTC and RBTC, it is obvious that they differ in their views about which group is bound to shrink. These views also bring different implications for the labor market itself and its participants. According to SBTC, we can expect widespread occupational upgrading and therefore better jobs for labor market participants on average. On the downside, workers with low skills are in a difficult position because demand for their services decreases. This might lead to higher unemployment rates or lower wages among low skilled workers. According to RBTC however, the average job is not necessarily getting better, since both high and low skilled occupations increase their numbers. For low skilled workers, this is good news: They have better chances to find jobs if occupations with low requirements don’t disappear. But this is paid for with an eroding middle class and a polarization of the labor market (Oesch 2013:16). Most of this thesis is dedicated to the question whether SBTC or RBTC is right about occupational change in Europe. I want to find out whether there is occupational upgrading or labor market polarization to be observed in European countries. The problem of unemployment will only be discussed briefly in chapter 9.

2. Mixed Evidence

As we saw in chapter 1, there are different theories about the effects of technological progress on occupational change. One argues that technological progress leads to general upgrading of the occupational structure, the other one expects to see a polarization of labor markets due to technological replacement of the middle class. These are obviously two contradictory assumptions, which cannot both be true at the same time for one country. To decide which theory is most convincing, we must therefore rely on empirical data. Only by testing the empirical implications of both theories, it is possible to come to a real understanding of how automation affects occupational change. Therefore, I want to present some of the most influential empirical studies on the topic in this chapter. First, I am going to summarize the different findings in chronological order, thereby giving an overview of recent developments in this field of research. Considering the contradictory theoretical assumptions, it is not very surprising that the empirical evidence on the topic is mixed as well. Therefore, in the second part of this chapter, I take the same studies again and examine them from a more analytical point of view: By comparing the samples and methods that were used in the studies, it should be possible to gain first clues about why different authors came to different conclusions.

From Upgrading to Polarization?

Until the end of the last century, the case seemed to be quite clear: All the available evidence was pointing towards uniform upgrading of the occupational structure in economically advanced countries (e.g. Autor et al. 1998; Berman et al. 1998). Since SBTC seemed to be a perfectly suitable explanation for this development, there was little reason to doubt neither the empirical observation nor the underlying theoretical reasoning. Therefore, it seemed to be a consensus that technology is replacing mostly low-skilled labor, while creating higher demand for highly skilled labor.

However, this consensus was seriously challenged in the new millennium by a paper published by Wright and Dwyer (2003). In it, they analyze the pattern of occupational change in the USA between 1963 and 2000. During the first decades of the analysis, they find everything as expected according to SBTC: Occupations with high wages expand rapidly, while those with low wages show relative decline. But towards the end of their sample period, they started to observe a different pattern: Now, starting in the 1980s, jobs at the bottom of the employment structure were suddenly declining less than those in the middle. They found a transition from occupational upgrading to labor market polarization.

Although Wright and Dwyer were not particularly interested in the effects of technology on labor markets in 2003, their findings had far-reaching consequences for this discussion when they were later combined with the insights of two other articles from the same year. One of them, written by Goos and Manning (2003), finds a similar move towards polarization in Britain between 1979 and 1999. Obviously, this was additional support for critics who didn't believe in SBTC. But they still needed an alternative theory to explain what could be observed. Luckily for them, this theory came in the right time: Still in 2003, Autor, Levy and Murnane published an article that introduced a revolutionary approach which was able to explain the observed patterns of labor market polarization: Routine-biased technological change (RBTC).

Together, these three articles built the foundation of many following research projects. Various countries were examined, diverse sample periods were chosen, and different methods were used in those studies. However, conclusions were usually not too different from each other: Starting their sample periods in the 1980s or later, most authors found evidence for labor market polarization, thus supporting the assumptions of RBTC.

The first breakthrough of the topic was achieved by Autor, Katz & Kearney who published an article with the title "The Polarization of the U.S. Labor Market" in 2006. This was the first article on labor market polarization that gained public attention internationally and it still remains one of the most cited articles on the topic to day. In it, the authors not only find further support for polarization regarding wages, but also show that the same pattern applies to education: The share of occupations with high and low educational requirements is rising, and the share of occupations in the middle is declining.

Not long after that, the analysis of European labor markets also started to gain more attention. To my knowledge, the first comprehensive analysis was conducted by Fernández-Macías and Hurley (2008) on behalf of the European Union. Using data from 23 different countries between 1995 and 2006, they show that labor market polarization is not consistent across countries. Although some countries clearly display a pattern of polarization, linear upgrading is just as clear in other countries. And, of course, they found many countries that fall between the two categories.

Unfortunately, the findings of Fernández-Macías and Hurley did not get much attention in the scientific community back then. Potential reasons might be their publication channel outside the usual scientific journals, or their forbearance to put their research in reference to the findings of the other authors mentioned above. Therefore, an article written by Goos, Manning and Salomons (2009) stepped into the breach and presented their own comprehensive analysis of labor markets in Europe. But even though they were working with a similar sample, they came to very different conclusions: They observed pervasive polarization of labor markets in Europe. Naturally, both conclusions were well founded. The inconsistent results were simply a product of different methods. Nevertheless, the article by Goos, Manning and Salomons received much more attention than the one by Fernández-Macías and Hurley, and the prevalent opinion became that labor market polarization was inevitable. Different empirical studies supported this view in following years (Autor 2015; Autor, Dorn, and Hanson 2015; Goos et al. 2014)

A few years later, however, the more nuanced view had its comeback. First, Oesch & Menes (2011) found significant variation in the degree of polarization between Britain, Germany, Spain, and Switzerland, which they traced back to different national institutions. This view gained further support by Dwyer and Wright (2012), who came to the same conclusion in an updated and expanded version of their original study from 2003, this time also including several European countries. Then, also, Fernández-Macías (2012) published another article, presenting roughly the same findings as before, but now choosing the right publication channels and putting his findings in proper context, thus gaining more attention than before. Other recent examples worth mentioning are the works of Oesch (2013) or Murphy and Oesch (2017) who both underline the importance of national institutions.

Due to these insights, a new controversy emerged in recent years. Suddenly, labor market polarization doesn't seem inevitable anymore, but there is neither a consensus about the actual degree of polarization in various countries, nor about the causes for differences between countries.

Comparison of Samples and Methods

As seen in the last section, there is no consensus about the effects of technological progress on labor markets in the USA and Europe. Some authors find evidence of pervasive polarization, others emphasize that there are different developments to be observed across countries. In this section, I want to compare the different ways how these contradicting conclusions were drawn. First, I focus on sample selection, then on the measurement of skills. A summary of recent influential articles and their relevant characteristics is presented in table 1 at the end of this chapter.

A first important observation can be made by comparing sample periods: In earlier years, most countries display a pattern of occupational upgrading, and later, they tend towards polarization. Thus, it seems like the increasing capabilities of machines slowly altered the patterns of occupational change. This is in line with the argument of RBTC: At first, machines could only replace labor in the bottom of the occupational structure, but later, machines learned to carry out more complex tasks, thereby enabling them to replace labor in the middle of the occupational structure. This transition from upgrading to polarization was examined in detail for the USA by Wright & Dwyer (2003) and Autor & Acemoglu (Acemoglu and Autor 2011). Thus, my first observation is that, according to the literature, there is probably a transition from upgrading to polarization over time.

More interesting, however, are comparisons of the countries under examination. By looking at table 1, it is easy to notice that most of the early research about the topic was conducted either in the USA or in Britain (e.g. Autor et al. 2006; Goos and Manning 2003, 2007; Wright and Dwyer 2003). In both these countries, a clear pattern of polarization was found after the 1980s, and following research continued to confirm these findings. Thus, it is fairly safe to assume that there is some consensus about the development of labor markets in Britain and the USA. But in other European countries, the case is not quite as clear. Even though Goos, Manning and Salomons (2009, 2014) claim to find a pervasive pattern of polarization in all European countries under scrutiny, various other authors disagree (Dwyer and Wright 2012; Fernández-Macías 2012; Fernández-Macías and Hurley 2008; Oesch 2013; Oesch and Menés 2011). These authors all share the view that there are different patterns of occupational change to be found across countries in Europe. In some cases, polarization is clearly visible, in other cases, polarization is only weak or not observed at all. Nevertheless, even these authors usually agree with the findings of early studies on the USA and Britain: These two countries are usually amongst the countries that display the most distinct pattern of polarization.
An often-cited explanation for the strong polarization in the USA and Britain is that their liberal institutions allow for more growth in the bottom of the employment structure than in other countries (Dwyer and Wright 2012; Fernández-Macías 2012; Oesch 2013; Oesch and Menés 2011). Other country-level characteristics are discussed as potential explanations as well, but for now, it is only important to state that there probably *are* differences between countries. This implies that we cannot assume a uniform effect of technology on labor markets. The effect apparently depends on certain characteristics of particular labor markets, which are most likely shaped by national institutions or other country-level characteristics. These country-specific determinants certainly deserve appropriate attention. Therefore, I will examine the relationship between national characteristics and occupational change in more detail in chapter 8 of this thesis.

These two aspects of empirical research (i.e. the selection of sample periods and country samples) seem to explain much of the variation in authors' conclusions about the effects of technological progress on labor markets. Accordingly, these points are also frequently discussed in the recent literature on the topic (e.g. Fernández-Macías 2012; Oesch 2013).

But there is another crucial aspect that has not gained much attention yet: the ranking of occupations. As we know, occupations are usually ranked according to their skill requirements in order to determine whether labor markets are upgrading or polarizing. Thus, the measurement of skills is one of the most central concepts in the literature. Yet, it is often used without the necessary consideration.

As we saw in chapter 1, the classic theories about technology-related occupational change are both speaking about skills originally: According to SBTC, low skilled occupations shrink, high skilled occupations rise. Later, RBTC claimed that occupations in the middle of the skill spectrum are disappearing faster than those at the bottom because they are more strongly based on routine tasks. To test these theories with empirical data, it is therefore necessary to categorize occupations according to their skill requirements. This is not an easy task however, since skills cannot directly be measured with conventional methods. Therefore, skill requirements are usually operationalized by using either educational attainments or wages (or both) as proxies in virtually all available studies. These two variables are expected to be the closest possible representation of skills, since education is essentially meant to improve one's skills, and higher skills should directly translate into higher wages (Autor et al. 2006; Fernández-Macías 2012).

Especially in older studies from before the turn of the millennium, education was frequently used to provide evidence for the theory of SBTC. The occupational upgrading, that was found thereby, was essentially an educational upgrading of the occupational structure. With the rise of RBTC however, things got mixed up a little. Now, the use of wages as proxies became more common, and more analyses started to show a pattern of polarization. Surprisingly however, not many authors seemed to be aware of this methodical issue. Most of them simply stated that the two proxies could be used interchangeably and would produce the same results in the end. This seemed plausible, since wages and education should both represent skills, and it could be shown that both of them correlate strongly with each other.

But only few studies actually used both variables in their analyses. Possibly, many authors relied on the results of Autor, Katz & Kearney (2006) who could show convincing evidence for polarization in the USA, using both income and education as proxies for skills. This seemed to be proof enough that income and education could in fact be used interchangeably. Therefore, most following studies only used wages in their analyses. At least two European studies however tested both proxies and came to interesting results: Fernández-Macías (2012), who found varying patterns of upgrading and polarization among different European countries, states that his findings are fairly consistent, independent of the proxy for skills that he uses. However, he also mentions that there is a slightly stronger tendency towards upgrading if skills are measured by education. These remarks are complemented by Oesch (2013) who also tested both proxies. He notes that, especially in Britain, patterns of occupational change vary depending on the proxy for skills. If measured by wages, Britain clearly displays polarization, but if measured by education, it clearly shows upgrading. Further investigating this issue, he finds that some occupations rank higher in the educational ranking than in the wage-ranking and vice versa: Occupations in production and crafts rank higher in wages than in education, and occupations in personal and social services rank higher in education than in wages. And since the former are declining and the latter are increasing, he observes different patterns of occupational change in Britain, depending on the proxy for skills.

Unfortunately, both Fernández-Macías and Oesch only treat these issues on a side note and don't seem to think of them as very important. Nevertheless, these are certainly significant findings that should be examined in more detail. Possibly, further investigation could help us understand why some countries display a pattern of polarization and others don't. Therefore, I am going to consider these issues in my own analysis which is presented in the following chapters.

Table 1: Summary of Recent Articles Concerning Upgrading/Polarization of Labor Markets (Selection)

Year	Author(-s)	Years covered	Countries covered	Occupations ranked by…	Findings
1998	Autor, Katz & Krueger	1940-1996	USA	Education	Upgrading
2003	Goos & Manning	1979-1999	Britain	Wages	Polarization
2003	Wright & Dwyer	1963-2000	USA	Wages	Upgrading → Polarization
2006	Autor, Katz & Kearney	1980-2000	USA	Wages & Education	Polarization (for both wages & education)
2007	Goos & Manning	1975-1999	Britain	Wages	Polarization
2008	Fernández-Macías & Hurley	1995-2006	23 European countries	Wages	Upgrading & polarization, depending on country
2009	Goos, Manning & Salomons	1993-2006	16 European countries	Wages	Polarization
2010	Acemoglu & Autor	1979-2007	USA	Wages	Upgrading → Polarization
2010	Oesch & Menes	1990-2008	GB, DE, ES, CH	Wages	Tendency towards polarization, but degree depending on country
2012	Dwyer & Wright	1995-2007	USA & 16 European countries	Wages	Tendency towards polarization, but degree depending on country
2012	Fernández-Macías	1995-2007	European Union: EU15	Wages & Education	Upgrading & polarization, depending on country (for both wages & education). Slightly stronger tendency towards upgrading if education is used.
2013	Autor & Dorn	1980-2005	USA	Wages	Polarization
2013	Oesch	1990-2008	GB, DK, DE, ES, CH	Wages & Education	Upgrading & polarization, depending on country (for both wages & education).
2014	Goos, Manning & Salomons	1993-2010	16 European countries	Wages	Polarization
2015	Autor	1979-2012	USA	Wages	Polarization
2015	Autor, Dorn & Hanson	1990-2007	USA	Wages	Polarization
2017	Murphy & Oesch	1970-2010	IE & CH	Wages	Upgrading & polarization, depending on country

3. Occupational Change

As we saw in chapters 1 and 2, there is no consensus about the patterns of occupational change in Europe. Contradicting theories and varying empirical approaches make it hard to come to generally valid conclusions. Therefore, I want to conduct my own analysis of occupational change in Europe in this chapter, while trying to consider all the issues that were raised in chapter 2 (sample selection and measurement of skills). I begin by describing my main source of data, the European Labor Force Survey, and the sample that I use. This is followed by a first examination of occupational change, based on standard occupational categories according to ISCO-classifications.

Data & Method

To analyze the labor markets of a large set of European countries, the European Labor Force Survey (ELFS) is the obvious choice as a source of data. It contains detailed survey data from all 28 member-states of the European Union as well as from Iceland, Norway, and Switzerland. By using large national samples, the survey is designed to produce data that covers the entire labor market of each country. Furthermore, the data produced by the ELFS is highly suitable for cross-country analyses, since all variables are standardized.

Naturally, my analysis only includes persons that were employed or self-employed at the time of the interview. This excludes persons that were unemployed or not in the labor force. Further, I exclude military occupations from my analysis, since they are employed in a sector that is entirely dependent on political decisions and therefore does not follow the same processes as the civil labor market.

For my purpose, the most important variable is clearly the one describing a person's occupation. The ELFS uses ISCO-classifications at the 3-digit level, which describes more than 100 different occupational groups in each country. Although I use this detailed data for creating mean scores of education- and wage-levels, I only use the 2-digit classification for the labor market analysis, because otherwise I would have to deal with many empty categories and issues of inconsistent categorization across countries. The 2-digit classification mostly solves these problems and still offers 28 (ISCO88) or 43 (ISCO08) occupational groups.

A major obstacle however is that the ISCO-scheme was completely revised in 2008, and the ELFS started to use the revised ISCO-version in 2011. This makes it impossible to directly compare the development of detailed occupations before and after 2011. But, since I don't want to ignore the most recent developments, I decide to choose a sample that allows to handle this problem as well as possible. In fact, I don't just use one sample, but two. One of them ranges from 1998 until 2010 and the other one from 2011 until 2015. This way, I can present separate evidence for the two periods, whenever I speak about detailed occupations, but cover the whole time period from 1998 until 2015 whenever I examine comparable variables such as education, wages, or even broad occupational groups.

Due to missing data or inconsistent categorization, I must omit several countries from my analysis[1]. This leaves us with a total sample of 23 European countries[2] over a 17-year time range from 1998 until 2015. All of these countries are members of the OECD; thus, we can assume a similar degree of economic and technological development. This is relevant, since labor markets in developing countries are obviously affected by technological progress in different ways than in economically advanced countries. Nevertheless, of course not all labor markets in my sample are exactly alike. There might be other differences which could be of importance here. I will come back to this in chapter 8. For now, it is only important that we assume a similar level of technological development.

Before the results of my analysis are presented, it is also important to understand the method that I use to examine different labor markets. At the foundation of my analysis lies the so-called "occupation-based approach" (Arntz, Gregory, and Zierahn 2016). This means that my units of analysis are not persons, but occupations. Therefore, I collapse the ELFS-dataset, creating a count variable for each occupation, separated by countries and years of observation. This allows us to calculate the share of employment that each occupation possesses in a country in a given year. For example, we could say that, in 1998, 10% of all employment in country X falls on occupation Y.

These percentages are central to my analysis: When I speak of growing or declining occupations, I always mean that an occupation's share of employment in a certain country is growing or declining. Thus, the absolute number of persons employed in a certain occupation might in fact be rising while the same occupation's employment share is decreasing. This would be the case if total employment in a country is increasing faster than the employment in a single occupation. Of course, the example also works the other way around: Absolute numbers of an occupation might decrease over time, but relative numbers increase if total employment in a country decreases even faster.

[1] Italy, Latvia, and Lithuania were omitted due to inconsistent categorization. Several other countries did not provide data in 1998 yet.

[2] Austria, Belgium, Britain, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Luxembourg, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, and Switzerland.

It is necessary to choose this approach based on relative numbers, since I want to compare the development of occupations in different countries, thereby giving each country the same weight. Otherwise, the size of national labor markets (or rather the size of national samples) would bias my results to an unacceptable extent.

Growing and Declining Occupations

My first examination of occupational change is rather a descriptive introduction than a test of any theories. In fact, it is the most basic analysis of occupational change there is: I simply want to show how single occupations increased or decreased their employment share over time. In figure 1, I do so by showing the mean employment shares of all major occupational groups provided by ISCO across the 23 countries. These mean values are plotted for different years in my sample, each with a gap of 4 years. Thereby, it is possible to assess the relative size of occupational groups as well as the change of their relative size over time.

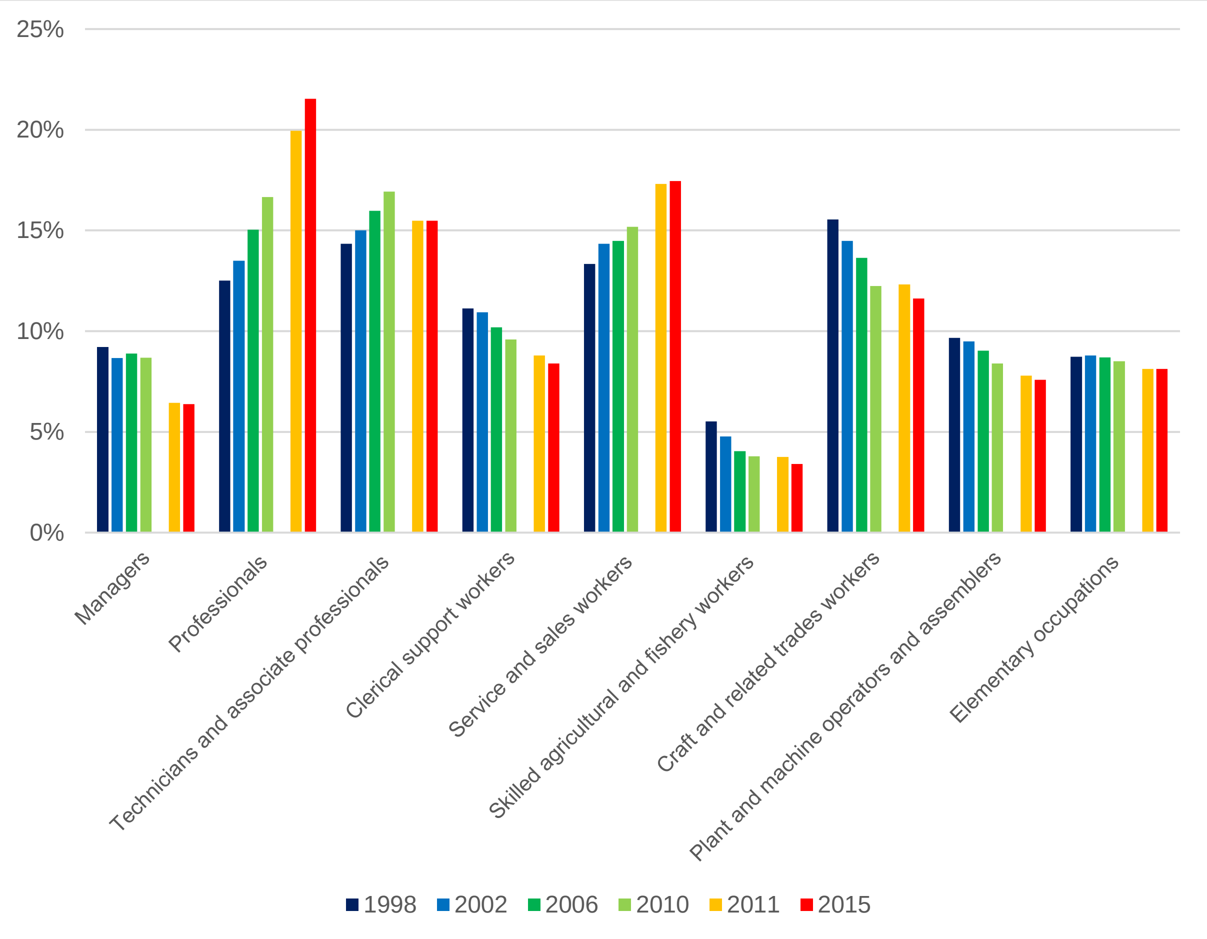
As noted before, ISCO-classifications used by the ELFS changed after 2010. Thus, it is not possible to draw any conclusions based on the change between 2010 and 2011 in figure 1. The gap between the two bars representing 2010 and 2011 is supposed to underline this issue. However, only the composition of major occupational categories was altered, not the description of categories themselves. Therefore, we can still compare developments of single major occupational groups between 1998 and 2010 with those between 2011 and 2015.

For example, we can say that the mean employment share of managers has been staying quite constant since 1998, both before and after the alteration of ISCO-classifications. But we can *not* say that the employment share of managers decreased between 2010 and 2011, even though the bar is lower in 2011 than in 2010. This change is solely due to the new classification system.

Other than the stability of managers' employment share, we observe a strong and steady increase in the mean share of professionals. In fact, professional occupations display the strongest expansion of all and thus became the largest occupational group in many countries. As the term "professionals" is not exactly self-explanatory, it might make sense to give a short description of this group: It consists of a variety of jobs such as scientists, engineers, doctors, teachers, and other highly trained occupations.

Other groups that typically display an increasing employment share are "technicians and associate professionals" and service workers. Although not as fast as managers, they both steadily increased their labor market share between 1998 and 2010. After 2011, however, this development seemed to come to a preliminary slow-down in both groups.

*Figure 1: Mean Employment Share of Major Occupational Groups (ISCO) on 23 European Labor Markets, 1998-2015**



* ISCO-classifications were altered between 2010 and 2011.

Naturally, if some occupations expand their share, others' need to shrink. This is clearly the case for four occupational groups: First, agricultural workers seem to disappear slowly. They already were by far the smallest group in 1998 and continue to become less numerous. Second, craft workers, who were the largest group in 1998, constantly decreased their share of the labor market until they only were on fourth rank in 2015. Third, machine operators also lost ground since 1998 and an end of this development is not conceivable in the data until 2015. Fourth, and perhaps surprisingly, another constant decline was observed for clerical support workers.

Finally, the share of elementary occupations did not change much on average. This group consists of occupations that "involve the performance of simple and routine tasks which may require the use of hand-held tools and considerable physical effort" (International Labor Office 2012). Typical examples are cleaners, or laborers in mining, construction, manufacturing, and transport.

As mentioned before, these are only mean values across the 23 countries in my sample. Developments in single countries might differ from these general patterns. Most often, however, national patterns relate very closely to the findings presented here. In almost all countries, the same occupational groups grow or decline. For example, professionals expand their share in all countries with only one exception (Britain). Also, agricultural workers are declining in all countries except in Britain and Ireland. There is only significant variation across countries, when we compare the development of managers and elementary occupations. Here, some countries display growth, others show decline (see appendix for detailed information).

After presenting this brief summary about the development of different major occupational groups, we now want to examine these occupations in more detail. Therefore, I leave the major occupational groups behind and conduct the same analysis using the 2-digit ISCO-classification. Instead of 9, we now have 28 (until 2010) respectively 43 (after 2010) categories. For obvious reasons, I don't want to describe each of these categories separately. Thus, I limit my analysis to the occupations that changed their employment share the most: I show five occupations with the highest average growth and five occupations with the steepest average decline. Since the newer ISCO-classification doesn't correspond with the old one on the 2-digit level, we must interpret our two samples separately this time. Results for the period between 1998 and 2010 are depicted in table 2, those for the period between 2011 and 2015 in table 3.

Table 2: Fastest Growing and Declining Occupations in 23 European Countries, 1998-2010

ISCO88	**Description**	**Mean growth***	**ISCO88**	**Description**	**Mean decline***
24	Other professionals	+1.96%	61	Skilled agricultural and fishery workers	-1.73%
34	Other associate professionals	+1.94%	41	Office clerks	-1.46%
51	Personal and protective services workers	+1.57%	72	Metal, machinery and related trades workers	-1.26%
21	Physical, mathematical and engineering science professionals	+1.17%	74	Other craft and related trades workers	-1.24%
23	Teaching professionals	+0.67%	13	Managers of small enterprises	-1.01%

* mean growth/decline of employment share in national labor markets

As we would expect based on the findings above, most growth in the period 1998-2010 comes from occupations summarized as "professionals". Three of the five fastest growing occupations belong to this category. The other two occupations belong to the "technicians and associate professionals" and the "service and sales workers" categories which also experienced growth as a whole. Unfortunately, both occupations on top of the list are not very informative, since they are only “other”-categories. To understand what they stand for, we must look at their content: “Other professionals” include business professionals, legal professionals, archivists, librarians, social scientists, writers, creative or performing artists, religious professionals, and public service administrative professionals. “Other associate professionals”, on the other hand, include among others: finance and sales associate professionals, business services agents, trade brokers, police inspectors, detectives, and artistic, entertainment and sports associate professionals.

On top of the list of fastest declining occupations until 2010 are, not surprisingly, agricultural workers. Here, 1-digit and 2-digit categories match each other exactly, since there is no other sub-category. The following three occupations are not very surprising either, since they all belong to major categories in decline. The last occupation however comes somewhat as a surprise: Managers of small enterprises decline quickly in general, although the major category of all managers remains almost constant. This must mean that managers of large corporations are increasing, thus indicating a possible shift of economic importance from small business to large corporations.

Table 3: Fastest Growing and Declining Occupations in 23 European Countries, 2011-2015

ISCO08	Description	Mean growth*	ISCO08	Description	Mean decline*
24	Business and administration professionals	+0.57%	71	Building and related trades workers	-0.40%
34	Legal, social, cultural and related associate professionals	+0.38%	44	Other clerical support workers	-0.31%
25	Information and communications technology professionals	+0.30%	41	General and keyboard clerks	-0.29%
22	Health professionals	+0.30%	33	Business and administration associate professionals	-0.22%
43	Numerical and material recording clerks	+0.21%	93	Laborers in mining, construction, manufacturing and transport	-0.19%

* mean growth/decline of employment share in national labor markets

Due to the revision of ISCO-classifications, many “other”-categories were not used by the ELFS anymore after 2010. Instead, new occupational groups were created, which accounts for the rise of the available number of 2-digit occupations from 28 to 43. Thus, the list of the fastest growing or declining occupations in table 3 is more detailed than the one before. However, these findings must be interpreted more cautiously, since only a period of four years is covered.

Again, we find three “professional” occupations among the ones that display the highest growth rates. They are business and administration professionals, information and communications technology professionals, and health professionals. Also, an occupation representing associate professionals ranks second on the list again. New however is the category of numerical and material recording clerks among the occupations with the fastest growth. This is somewhat surprising, since the major category of clerical workers is generally in decline.

As we see on the right side of table 3, the growth of numerical and material recording clerks is offset by the decline of two other categories of clerical occupations. Declining the most, however, is the share of building and related trades workers. Thus, the three occupations displaying the most decline after 2010 all belong to major categories that are shrinking in general. On the other hand, the other two occupations on the list are part of major occupational groups, that stay more or less constant in general. Interestingly, associate professionals appear in both sides of table 3: Business and administration associate professionals are among the occupations that decline the most.

Reviewing this evidence, we come to a basic understanding of occupational change. We now know which major occupational groups are expanding their share on European labor markets and which ones are in decline. Also, we know which occupations are growing or declining the most. Our findings in this chapter are coherent with theories on technology-based occupational change and confirm the findings of previous empirical studies (e.g. Autor 2015; Fernández-Macías 2012; Oesch 2013; Oesch and Menés 2011). Therefore, we find support for the claim that highly educated professionals and interpersonal service workers are expanding their shares the most, since their work is not easily automated, and some of them even profit from complementary effects (Autor 2015). The case of quickly increasing numbers of information technology professionals is a clear example for these effects. And, on the other side, our findings also support the idea that machines can more easily replace large numbers of agricultural workers or craftsmen due to their low skill requirements (Acemoglu 2002; Fernández-Macías and Hurley 2017) or high routine content (Autor 2015). Therefore, these insights might give us a first idea about what kind of occupations are affected by technological replacement and what kind are growing due to complementary effects. However, we still don’t know why these occupations are affected in the ways they are: Are we observing a skill-biased or a routine-biased occupational change? And, closely related to this question: Is this leading to an upgrading or to a polarization of labor markets? To answer these questions, we need further evidence.

4. Changes in the Educational Structure

As I have discussed in chapter 2, the measurement of skills is a crucial factor when assessing the pattern of occupational change in a country. In the existing research, there is some evidence suggesting that, if occupations are ranked by their wages, there is stronger tendency towards polarization than if they are ranked by their educational requirements. Therefore, I want to examine the patterns of occupational change in our sample twice: First, I rank occupations by their educational requirements in this chapter, then by their mean wages in the next chapter.

Observing Patterns of Occupational Change

My following analyses are based on the same data as before: I use the ELFS-data of all 23 countries in our sample and calculate the national employment share of each occupation for different points in time. All occupations are measured on the ISCO 2-digit level. For each occupation, I then calculate the mean educational level of all its representatives, separated by country. Educational levels of individuals are measured by the six ISCED-97 values, as they are included in the ELFS.

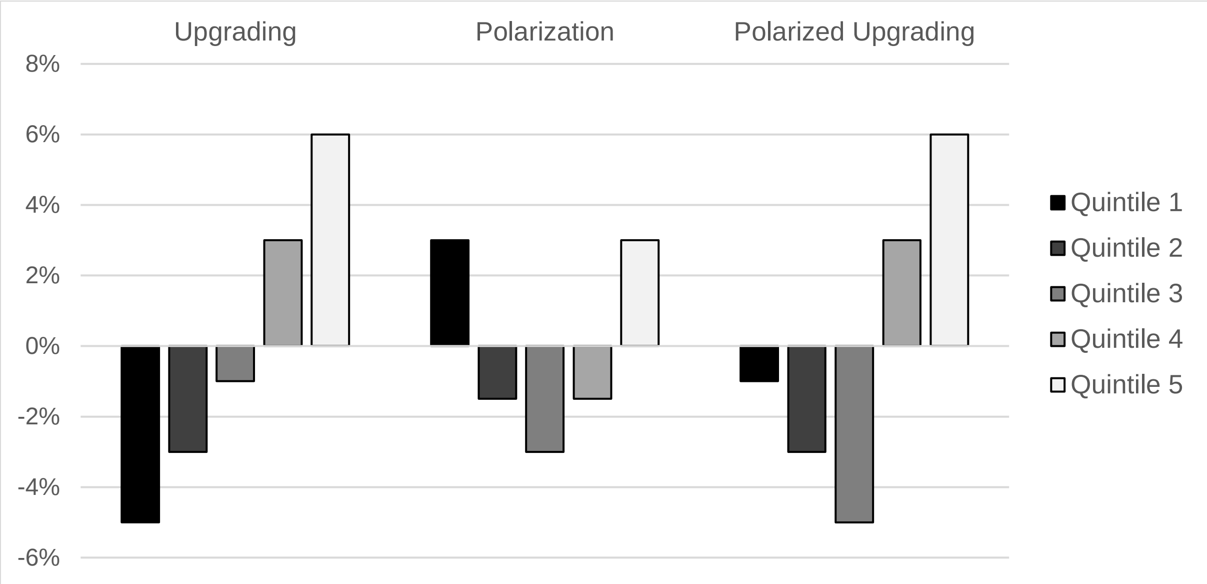
Next, I sort occupations by their mean educational levels and divide them into five different groups in each country. Each of these groups is containing approximately 20% of all employment in a country at the beginning of our sample period in 1998. These quintiles each represent a specific part of a country's labor market: For example, each quintile 1 includes all occupations with the lowest educational scores found in a country. Respectively, each quintile 5 stands for the 20% of employment in 1998 that was employed in occupations with the highest educational requirements.

By observing the change in size of each of these quintiles, we can now examine patterns of occupational change. If, for example, quintile 5 in country X has grown by 5% between 1998 and 2015, it means that occupations with the highest educational requirements have increased their employment share by 5% in this country. Naturally, another quintile with lower education must be shrinking in this case, since we are looking at relative shares of total employment.

The pattern of occupational change is then determined by which quintiles grow and which ones shrink. In figure 2, three hypothetical examples are depicted. In the left example, we would observe a perfect case of occupational upgrading: Occupations with high educational requirements have increased their share and those with low requirements have declined in relative terms. The gradual transition from quintile 1 to quintile 5 would indicate an almost perfect correlation between educational requirements and job growth.

In the middle example, however, things look quite different: Here, both quintiles 1 and 5 are increasing their employment share, while quintiles in the middle are in relative decline. Thus, according to this example, occupations with highest and lowest educational requirements are expanding and occupations in the middle of the employment structure are slowly disappearing. This would be a typical pattern of polarization.

Figure 2: Hypothetical Patterns of Change in Employment Share



These are the two patterns that are usually discussed in the literature. However, there is another pattern which is frequently found in empirical studies. It lies somewhere between upgrading and polarization, since it displays characteristics of both: As in upgrading patterns, the highest quintiles are growing the most, and all lower and middle quintiles are declining. But like in polarizing patterns, the decline is considerably faster in middle than in bottom quintiles. In the literature, there is no consensus about how this pattern should be categorized. Some authors call it rather an upgrading pattern (Oesch 2013), others clearly focus on the polarizing aspect (Goos et al. 2009, 2014). This might partly be causing the observed discrepancy in the results of these authors. For this reason, I think that this pattern should have a name on its own. I am going to call it a pattern of “polarized upgrading” in the rest of this thesis.

This approach of observing occupational change was first used by Wright and Dwyer (2003) and later became the standard model to examine patterns of occupational change. It is important to remember that this is an occupation-based approach. Thus, I am not ranking and categorizing individuals but only occupations, based on their mean values regarding education (or wages in the next chapter). This means that, if an occupation belongs to quintile 1 in 1998, it will remain there for the rest of the sample period. This is necessary to measure the growth or decline of a group of occupations, and not the change in people's average education over time.

Due to my sample selection however, there is one major challenge when applying this approach: Since ISCO-classifications were altered in 2011, quintiles could not easily be observed continuously from 1998 until 2015. Freshly introduced occupations, that were not considered in 1998, must be newly categorized, and others, whose description was altered, must be revaluated. Therefore, I create new quintiles in 2011, each containing approximately 20% again. Then, I measure the change of these new quintiles until 2015.

In the following presentation of my results, I simply add together the change of quintiles before and after 2011. One might object to this practice, since the quintiles don't necessarily represent the same group of occupations anymore and therefore making general statements about groups would not be defensible. But, as I find, the relative order of occupations remains the same in virtually all countries during my sample period. Therefore, very similar occupations are found in the same quintiles before and after 2011, which allows me to summarize my findings for the whole sample period. This is further supported by the finding that patterns of occupational change stay constant over time, even over the classification-break between 2010 and 2011.

Educational Upgrading

Before we examine the patterns of occupational change themselves, it seems reasonable to briefly describe the typical classification of occupations into educational quintiles. This way, we don't just speak about quintiles as empty constructs, but it becomes clear what they actually stand for. In table 4, a typical composition is presented.

Table 4: Typical Composition of Educational Quintiles

Quintile	Major Occupational Groups (ISCO 1-digit)
5	Professionals; (Managers)
4	Managers; Technicians and associate professionals; (Clerical support workers)
3	Clerical support workers; Service and sales workers; (Craft and related trades workers)
2	Service and sales workers; Craft and related trades workers; (Skilled agricultural and fishery workers)
1	Skilled agricultural and fishery workers, Plant and machines operators and assemblers; Elementary occupations

When analyzing the composition of educational quintiles, it is immediately noticeable that quintile 5 is almost entirely occupied by professionals in most cases. With the exception of a few countries where managers also belong to quintile 5, professional occupations are therefore clearly requiring the highest educational attainments of all. Most managers, however, are found in quintile 4 among most technicians and associate professionals. In some cases, clerical support workers also rank in quintile 4, but most of the time they find themselves in the middle of the educational structure in quintile 3. This is also where a large part of service and sales occupations are categorized, but these are almost equally distributed between quintiles 2 and 3, varying from country to country. Similarly distributed are craft occupations, but these are more often found in quintile 2 than in quintile 3. Finally, among the 20% of employment with lowest educational requirements, we usually find occupations in agriculture, machine operators, and elementary occupations. Although the classification of occupations into quintiles is very similar across all countries in our sample, it is important to note that there might be some country-specific features that differ from this general pattern.

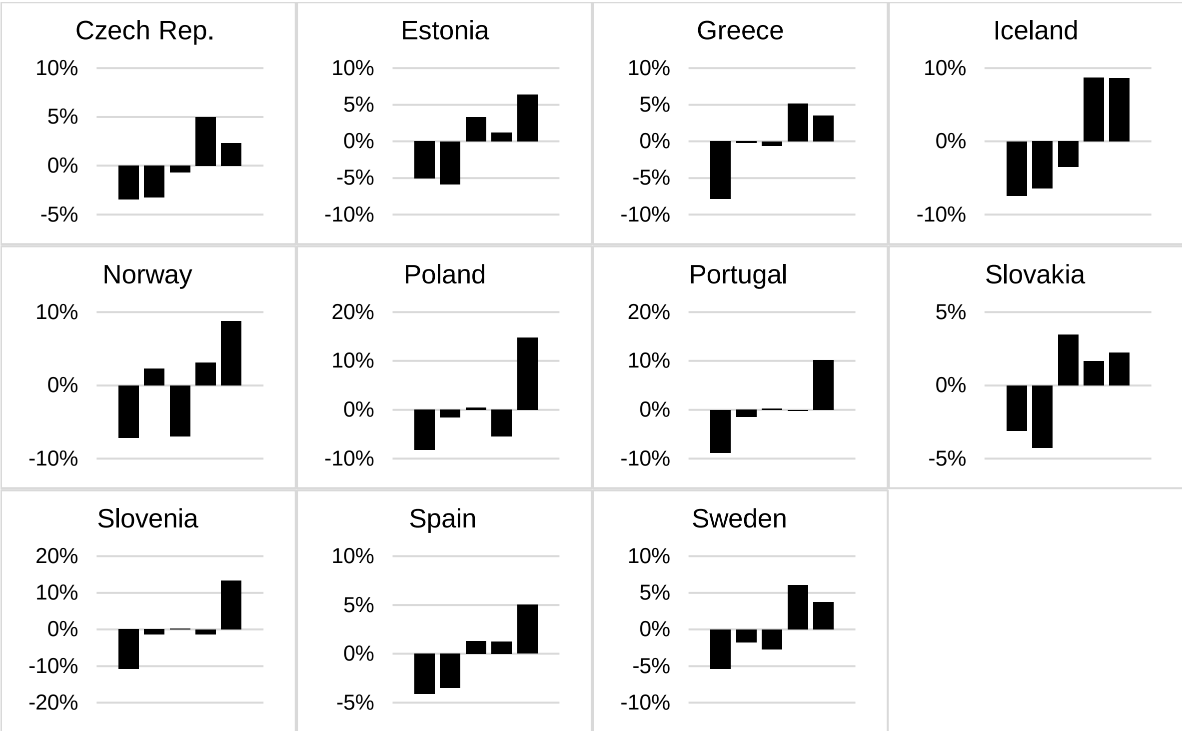
With this in mind, we can now move on to the examination of country-specific patterns of occupational change. Several interesting observations can made here. As we see in figure 3, quintiles 4 and 5 have grown in virtually all countries between 1998 and 2015. Thus, my evidence supports the theoretical claim that highly educated labor is expanding, possibly due to complementary effects with technology that lead to higher productivity.

But looking at the lower quintiles 1-3, we find quite different patterns across countries. Eleven of our 23 countries display a clear pattern of educational upgrading: The lowest quintiles are declining the most, and the highest quintiles are growing the most, while the middle quintile typically remains rather constant. Thus, we observe a more or less perfect linear relationship between educational requirements and job growth in these countries. This would clearly support the thesis of SBTC.

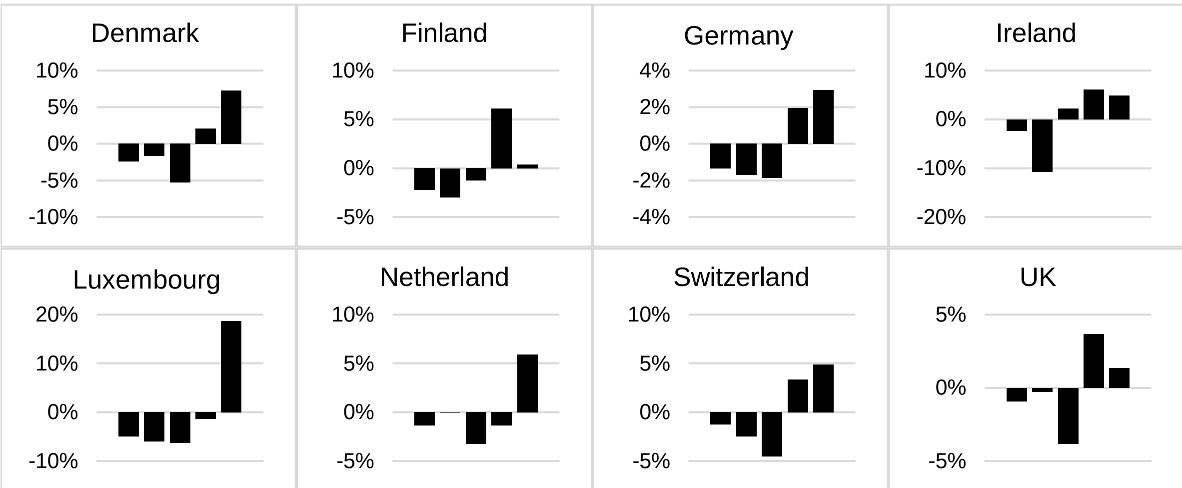
Nevertheless, a group of ten other countries is showing signs of labor market polarization. They all display the U-shaped pattern of occupational change that is a distinct feature of polarization. However, only two countries (Belgium and France) actually include a relative growth of quintile 1 and therefore display a classic pattern of polarization. The other eight countries all show what I call a pattern of polarized upgrading. In these countries, all growth is based on highly educated occupations in quintiles 4 and 5 while all other quintiles are declining. However, occupations in the middle of the educational structure are declining even faster than those at the bottom in these countries.

Figure 3: Relative Change in Employment Share by Education Quintiles, 1998-2015

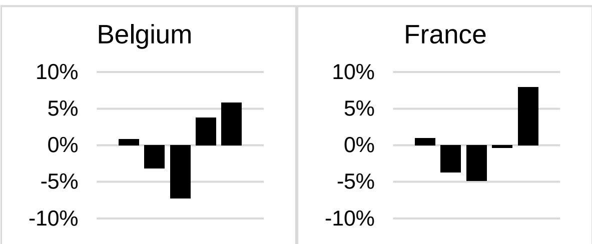
Upgrading:



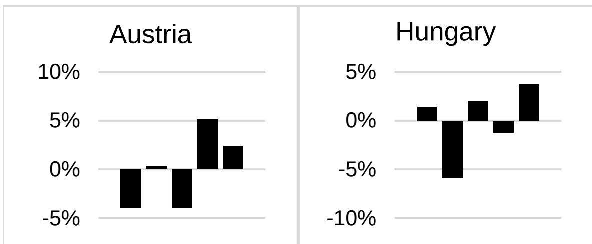
Polarized Upgrading:



Polarization:



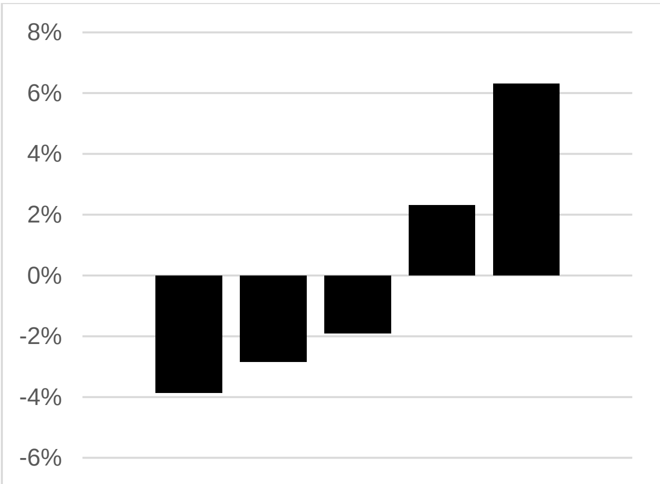
Other Patterns:



This doesn't mean however that polarization is not a relevant issue in these cases. If the middle class is disappearing twice as fast as the lower class, there is still going to be a wide gap in the occupational structure for a long time. But we should keep in mind that, with the exception of Belgium and France, no country displays a pattern of polarization in the narrow sense that includes relative job growth in quintile 1.

Overall, this evidence seems to favor the theory of occupational upgrading, even though there are some countries with a tendency towards polarization or polarized upgrading. This view gains further support if we estimate the average pattern of occupational change across all 23 countries in our sample. As shown in figure 4, the average pattern is clearly one of occupational upgrading if occupations are ranked by educational requirements: Occupations with low requirements decline, and those with high requirements expand. This average pattern is also constant over time: It shows up in each 4-year period between 1998 and 2015[3].

Figure 4: Mean Relative Change in Employment Share by Education Quintiles, 1998-2015



Thus, the evidence shown in this chapter clearly supports the theory of SBTC: We find that occupations with high educational requirements display strong growth in all examined countries, while occupations with low educational requirements show decline in most countries. On average, we even find an almost linear, positive relationship between educational requirements and change in employment share, exactly as predicted by SBTC: The higher the educational requirements of an occupation, the higher its increase in employment share.

[3] Due to the alteration of ISCO-codes after 2010, the periods are: 1998-2002, 2002-2006, 2006-2010, and 2011-2015.

5. Changes in the Wage Structure

I have shown in the last chapter that, if we measure skills by educational requirements, we can observe various patterns of occupational change in Europe, but an overall trend towards occupational upgrading. In this chapter, I am going to repeat the same analysis using mean wages as proxies for skills instead of educational attainments.

Adding Data on Mean Wages

Again, I use the same ELFS data sample as before, measuring employment shares of occupational groups at the ISCO 2-digit level. Unfortunately, data on income is only available for all countries in the ELFS after 2009, and even then, it is measured rather imprecisely and remains fragmentary. Therefore, I aggregate income data provided by the EU-SILC[4] survey and match it with our ELFS-data on occupational change. This way, I assign mean wages to each occupation in our sample, separated by country. In 20 of 23 countries, this approach produces data on wages for all relevant occupations. Only for Greece, no income data is included in the EU-SILC at all. For Portugal, several ISCO88-categories are missing and therefore I can only use income data for Portugal after 2010. The opposite is true of Ireland: I can only use income data until 2010 because it is incomplete after that.

After adding mean wages to our dataset, I create quintiles the same way as described in the previous chapter, only replacing mean education by mean wages this time. Thus, quintile 1 in each country now represents all occupations with the lowest mean wages that together account for approximately 20% of all national employment in 1998. Accordingly, each quintile 5 represents the best paid occupations in each country, also containing roughly 20% of employment in 1998.

When examining the composition of wage quintiles in table 5, several differences stand out in contrast to the educational quintiles used in the previous chapter. First, occupations tend to scatter more strongly across countries in wage quintiles than in educational quintiles. Thus, it seems that the educational rankings of occupations are quite similar across countries in our sample, while the respective wage rankings display more variation in comparison. In consequence, many occupational groups are listed twice in table 5, since they belong to different quintiles in different countries without any clear tendency towards one quintile or another.

[4] European Union Statistics on Income and Living Conditions

Table 5: Typical Composition of Wage Quintiles

Quintile	Major Occupational Groups (ISCO 1-digit)
5	Managers; Professionals
4	Professionals; Technicians and associate professionals
3	Technicians and associate professionals; Plant and machines operators and assemblers; Craft and related trades workers; Clerical support workers
2	Clerical support workers; Service and sales workers; Craft and related trades workers; Plant and machines operators and assemblers; (Skilled agricultural and fishery workers)
1	Service and sales workers; Skilled agricultural and fishery workers; Elementary occupations

Despite the broader allocation of occupations, some groups clearly occupy different positions in the wage structure than in the educational structure. For example, a significant change can be observed in the top quintiles: The data shows that virtually all professionals are among the occupations with highest educational requirements, therefore placed in quintile 5. Measured by wages however, many of them are replaced by managers and fall down into quintile 4. Some managers apparently earn more than professionals, although their educational requirements are lower on average. A similar effect, but at the other end of the scale, can be observed for machine operators: Although they are usually found in quintile 1 among the occupations with lowest mean education, their wages rank much higher and place them in quintiles 2 and 3 of the wage structure.

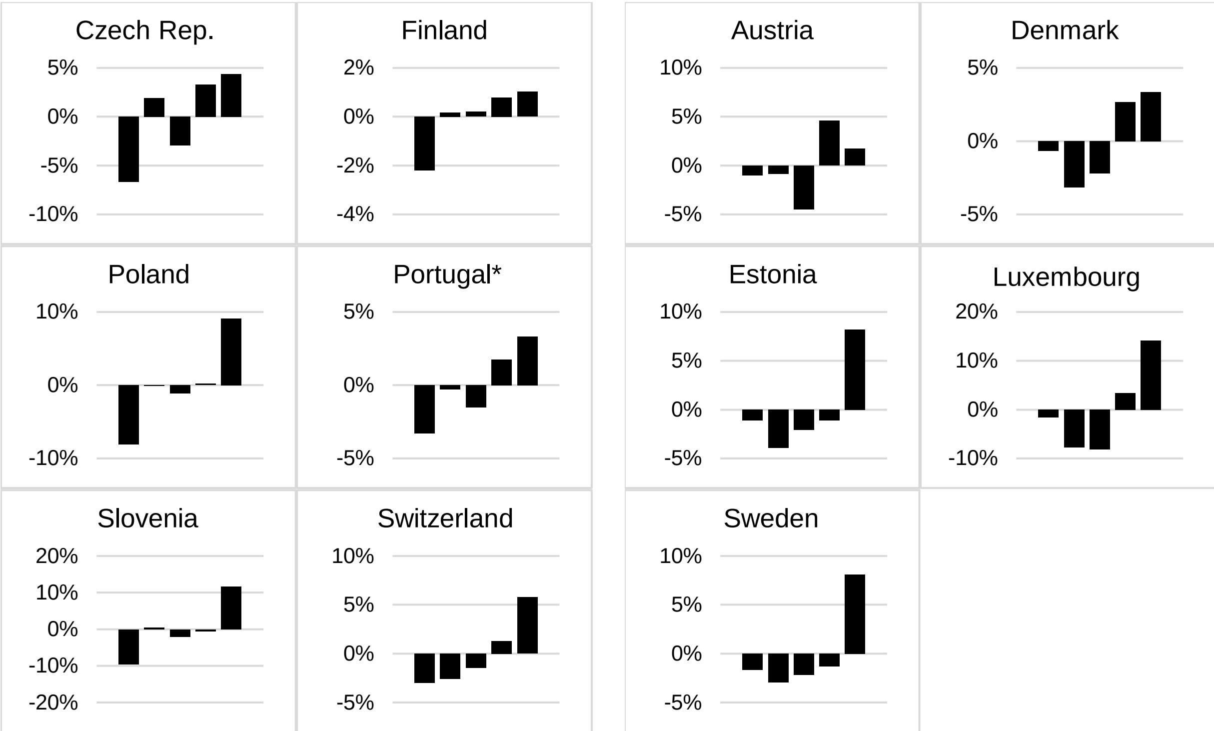
On the other hand, clerical occupations are usually ranked considerably lower in the wage structure than in the educational structure. While they are typically categorized in educational quintile 3 and 4, they only belong to wage quintiles 2 and 3. The same pattern also applies to service occupations: Ranked by education, they are found in quintiles 2 and 3, but measured by wages, they fall down into quintiles 1 and 2.

Polarized Upgrading in Wages

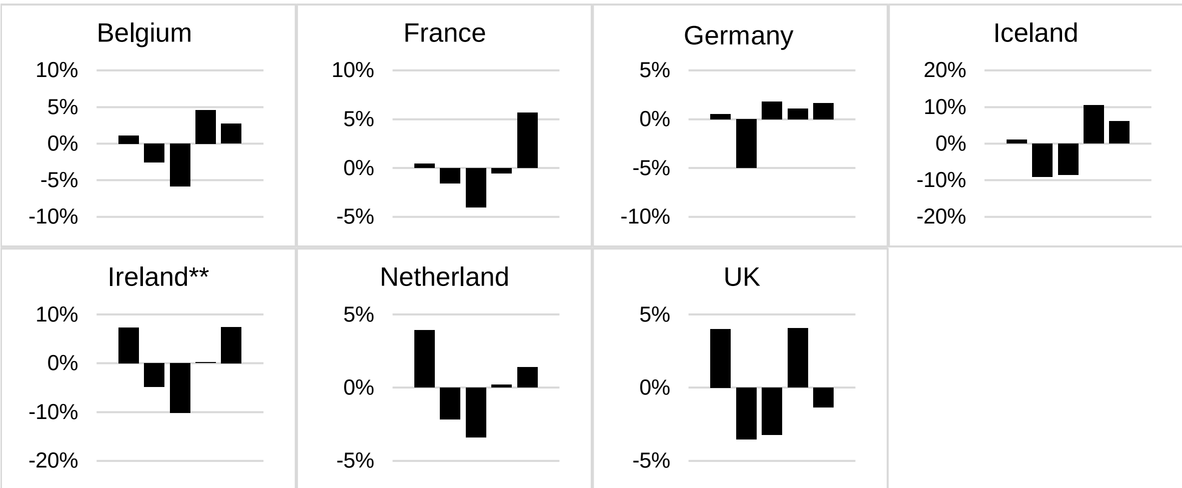
Considering the fact that wage quintiles contain different occupations than educational quintiles, one might also expect differing patterns of occupational change, depending on which quintiles are examined. As shown by figure 5, this expectation is confirmed by the data: Although quintiles 4 and 5 are growing again in most countries between 1998 and 2015, the development in lower wage quintiles looks quite different than in educational quintiles. Instead of only two, seven countries now display a growth in quintile 1, meaning that the lowest paid occupations in these countries increased their employment share. Simultaneously, middle quintiles declined in all these seven countries, thus displaying a clear pattern of labor market polarization.

Figure 5: Relative Change in Employment Share by Wage Quintiles, 1998-2015

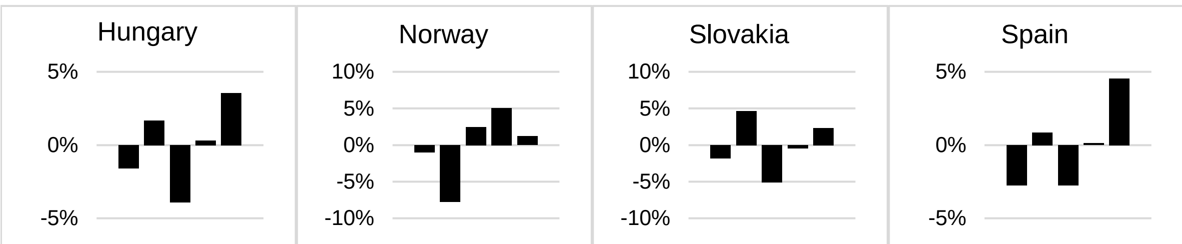
Upgrading: **Polarized Upgrading:**



Polarization:



Other Patterns:



*only period 2011-2015 covered for Portugal

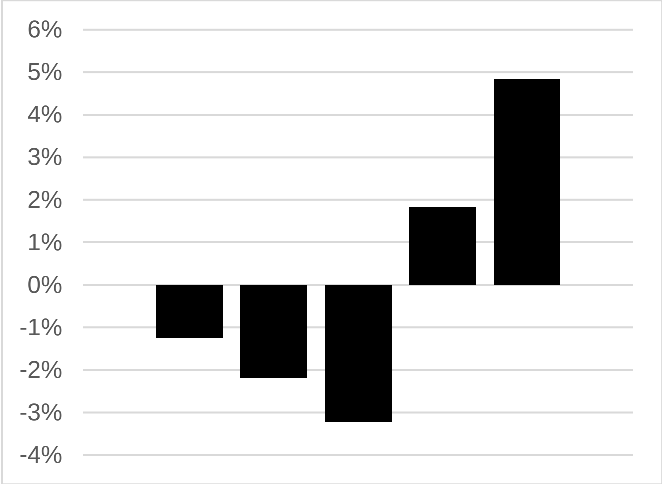
**only period 1998-2010 covered for Ireland

Among the countries with the most pronounced polarized pattern are Ireland, the Netherlands, and the UK, each showing growth of quintile 1 by 4% of total employment or more.
Again, we also observe some countries where all lower quintiles are declining, but decrease is significantly faster in the middle than at the bottom of the wage structure. Therefore, these five countries display a pattern of polarized upgrading. Finally, instead of eleven, only six countries display a clear pattern of occupational upgrading if occupations are ranked by wages.

Although many countries obviously change their pattern depending on the measurement of skills, it is remarkable that most countries don't change their pattern completely. With the exception of Iceland, no country shows clear polarization using one measurement and clear upgrading using the other one. Four countries however changed from a pattern of polarized upgrading to one of clear polarization. Equally, another four countries changed between patterns of clear upgrading and polarized upgrading. It therefore seems plausible that these two ways of measuring skills are somehow related. But still, this is far from being proof that they actually measure the same concept.
Overall, these findings imply a significant shift towards polarization if occupations are ranked by wages rather than educational requirements. Compared with the patterns based on educational quintiles, we now find more countries displaying clear polarization and less countries showing clear upgrading, while the number of those in between remains almost the same. Thus, it is clear that there is a stronger tendency towards polarization in a country's wage structure than in educational requirements of occupations. This is in line with the findings of Fernández-Macías (2012) and Oesch (2013), as described in chapter 2.

However, I can make a considerably stronger statement than Fernández-Macías and Oesch if I estimate the average change of wage quintiles. The results are depicted in figure 6: I find a perfect example of polarized upgrading as the average pattern of occupational change if occupations are ranked by wages. There is not only a slightly stronger tendency towards polarization, but there is systematic divergence from the patterns which are measured by education. Quintiles 1, 2, and 3 are all declining, but quintile 3 is declining the most and quintile 1 the least. Middle class occupations are therefore disappearing faster than lower class occupations, opening up a gap in the wage structure. On the other side, quintiles 4 and 5 are both expanding as expected, with the top wage-earning occupations growing the most. Again, this average pattern shows in every 4-year period between 1998 and 2015. Furthermore, the pattern becomes more pronounced over time, displaying more decline in the middle and more growth at the top.

Figure 6: Mean Relative Change in Employment Share by Wage Quintiles, 1998-2015



Therefore, it seems that occupations in the middle of the wage structure are in fact most affected by technological replacement on average. Occupations with the lowest wages are certainly also affected in many cases, but apparently less than those with medium wages on average. This clearly supports the theory of RBTC which claims that most routine occupations are found in the middle of the occupational structure.

6. Why Two Different Trends?

I have shown in the two previous chapters that there is a tendency towards occupational upgrading in Europe if occupations are ranked by educational requirements, but a tendency towards polarized upgrading if occupations are ranked by wages. This seems to be problematic, since education and wages should both act as proxies for the same underlying concept, which is skills. As we remember, both SBTC and RBTC use skills to describe which occupations are affected by technological change: SBTC assumes that occupations with the least skill requirements are most easily replaced by machines, and RBTC predicts most decline in routine occupations which are found in the middle of the skill spectrum. Thus, our findings seem to be inconclusive. While upgrading patterns based on education support the claims of SBTC, more polarized patterns based on wages provide evidence for RBTC. In this chapter, I want to examine the cause of these conflicting observations in more detail and discuss the theoretical implications of my findings.

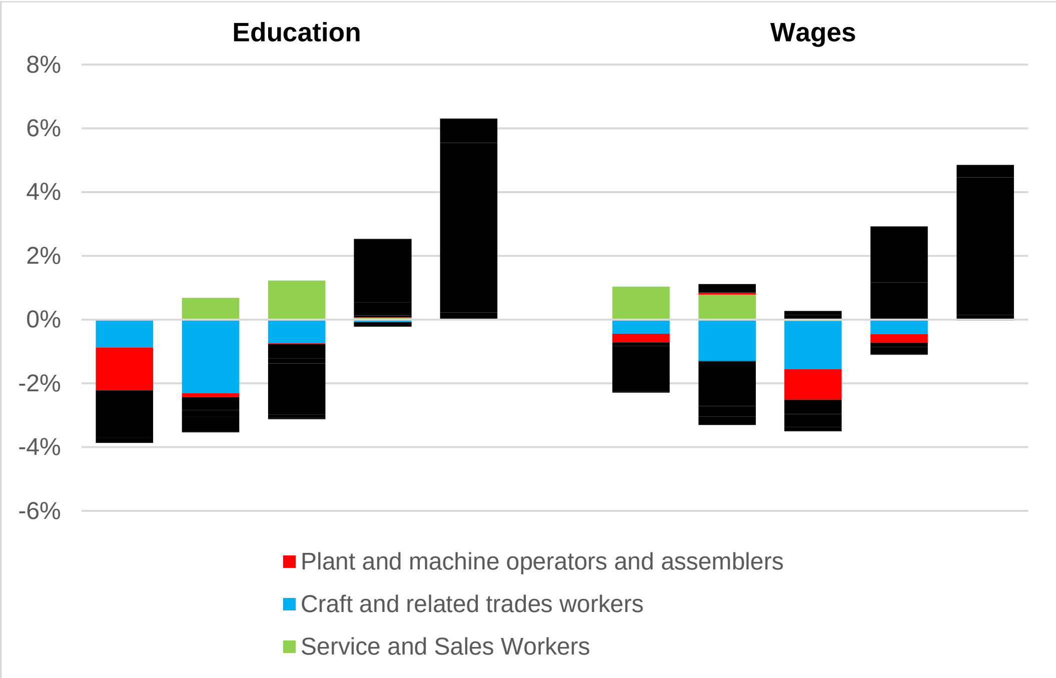
Composition of Change across Quintiles

As we saw in chapters 4 and 5, the educational structure and the wage structure of occupations are not identical in European countries. Several occupations rank higher in one than in the other and vice versa. Clearly, these discrepancies must be responsible for the diverging patterns of occupational change that we find between the two skill-measurements. If, for example, one strongly declining occupation requires very low education but earns medium wages, this occupation could potentially explain the whole difference between patterns of occupational change in the two structures. Or, of course, the difference could also be caused by a growing occupation with medium education and low wages.

In our case however, we have several candidates that could potentially cause this discrepancy: Service workers, machine operators, and clerical workers are all shifting their position between low and medium quintiles, depending on whether quintiles are created using education or wages. Service and clerical occupations rank higher in education than in wages, and machine operators rank higher in wages than in education. Therefore, all of these occupational groups could potentially cause a shift from upgrading in education towards polarization in wages. However, we already know from chapter 3 that service jobs are generally expanding, while clerical jobs and machine operators are declining in most countries. Thus, only service jobs and machine operators could explain the shift towards polarization in the wage structure. The decline of clerical occupations, on the other hand, could only be a potential explanation for polarized patterns in the educational structure.

That said, we also have to consider major occupational groups that are distributed across different quintiles as potential causes for the different effects that we observe. The reason is that, in these cases, the composition of quintiles might also differ on the ISCO 2-digit level, even though it looks the same on the 1-digit level. If, for example, craft workers are found with similar shares in both quintiles 2 and 3, there might be some 2-digit craft occupations in education quintile 2 and wage quintile 3, or vice versa. And if the craft occupations in wage quintile 3/education quintile 2 decline faster than those in wage quintile 2/education quintile 3, this could partly explain the shift towards polarization in the wage spectrum.

Figure 7: Composition of Occupational Change across Quintiles, 1998-2015



In figure 7, the average pattern of occupational change across all countries in our sample is broken down into major occupational groups. For reasons of clarity however, only relevant groups are highlighted with colors. As can be seen, three major occupational groups are mainly causing the observed discrepancy in patterns of occupational change. First, machine operators only display significant decline in quintile 1 in the educational structure, but in quintile 3 in the wage structure. Second, craft workers are responsible for decline across all quintiles 1-4, but to different extent: Regarding wage quintiles, decline of craft workers is clearly strongest in the middle. But regarding education, decline of craft occupations is mostly limited to lower quintiles. Together, machine operators and craft workers already account for more than half of the decline in low education and medium wage quintiles. Third, service jobs are generally expanding in the middle of the educational, but at the bottom of the wage structure. Thus, growth of service jobs adds to the lower decline of machine operators and craft workers in the same quintiles, leading to relatively low decline in the middle of the educational distribution and at the bottom of the wage structure. Together, the impact of these three occupational groups on different positions in the wage and the educational structure can therefore explain why we observe a tendency towards upgrading in one and a tendency towards polarized upgrading in the other.

This must mean that, at least for these three occupational groups, education and wages cannot be used interchangeably as proxies for skills. They clearly don't measure the same concept and must therefore be treated separately by all researchers. Doing so not only brings us to a more accurate description of occupational change, but also dissolves the apparent contradiction between SBTC and RBTC: If we accept educational and wage structures as separate, independent descriptions of labor markets, then both theories can be right. SBTC correctly predicts general developments in the educational structure and RBTC does so regarding the wage structure.

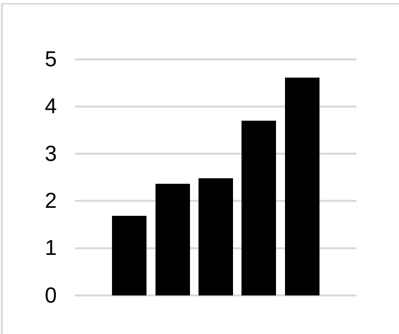
Technical Feasibility and Occupational Change

Although we can dissolve the apparent contradiction between SBTC and RBTC by treating education and wages separately, doing so does not solve all theoretical problems. In fact, it brings up a new problem which is even more serious than the old one: If SBTC and RBTC are both correct, we don't really know anymore what makes occupations grow or decline. So far, we only know that occupations with low education and medium wages are declining the most. But are they declining for the same reason? And if yes, is it skills, routine content, or something completely different?

Clearly, the obvious answer to these questions would be to assume that occupations with low education or medium wages are on average most susceptible to automation because they are most easily automated. Nothing seems to contradict this intuition: It might well be true that the tasks of machine operators and craft workers are actually most easily emulated by machines and simply happen to rank higher in wages than in education. But without explaining what exactly makes these occupations most susceptible to automation, this is simply a reference to an empty theoretical concept.

Therefore, we must test different propositions for characteristics that make occupations susceptible to automation. First, I follow the suggestion of SBTC and examine whether low skill requirements are the common cause that make occupations susceptible to automation. Of course, I should also consider both measurements of skills in this case, as I have postulated in the last section. One measurement, however, is out of the question in this case. Skills measured by wages are clearly not the cause for decline, since occupations in the middle of the wage structure are declining the most. Therefore, skills can only possibly explain occupational change if they are measured by educational requirements. In this case, at least one match between theory and empirical evidence is self-evident: According to my analyses, occupations with low requirements are declining the most and highly educated occupations the least. This would support the view that occupations with low educational requirements are most easily automated. But accepting low educational requirements as the reason for decline would further imply that occupations with medium wages must on average display lower educational requirements than occupations with low or high wages in the beginning of our sample period. In any other case, susceptibility to automation cannot be measured appropriately by educational requirements. But as we find in figure 8, occupations in wage quintile 3 are usually not displaying the lowest educational requirements. Instead, there seems to be a linear relationship between education and wages: Occupations that require higher education, also earn higher wages on average. Therefore, educational requirements must be ruled out as a measurement of an occupation’s susceptibility to automation.

Figure 8: Mean Educational Requirements across Wage Quintiles, 1998



Another obvious candidate that I want to test is routine task intensity, as proposed by RBTC. Assuming that this measure can explain susceptibility to automation, we would expect it to be highest for occupations in wage quintile 3 and for those in educational quintile 1. The problem however is that routine task intensity is not as easily measured as average education or wages. Luckily however, several measures are at hand. I first test the same variable that was originally constructed by Autor, Levy and Murnane (2003) and then used with slight variations in many subsequent studies supporting RBTC (Acemoglu and Autor 2011; Autor and Dorn 2013; Autor et al. 2006; Goos et al. 2009, 2014). This variable is based on the US Department of Labor's Dictionary of Occupational Titles (DOT) which provides detailed descriptions of the task content of more than 12’000 different occupations. To create the variable, these descriptions are number-coded across different dimensions by the researchers and then aggregated into a standardized scheme of occupations. In my case, I use a version of this variable provided by Autor and Dorn (2013) which includes values on routine task intensity for 330 different occupations. Even though these occupations are not originally coded according to the ISCO-scheme, I choose this variable for the sake of precision, completeness, and public availability[5].[6]

Figure 9: Mean Routine Task Intensity (Autor & Dorn) across Educational and Wages Quintiles, 1998

In figure 9, the average routine task intensity of occupations is displayed for all educational and wage quintiles. Using the variable provided by Autor & Dorn (2013), we find that occupations with medium wages contain most routine tasks and should therefore be most susceptible to automation. Occupations in wage quintiles 1 and 5 are considerably less routine-intensive and therefore less susceptible to automation. Although not matching perfectly, we could use this distribution of routine task intensity as an explanation for polarization in the wage structure.

The same pattern however can be observed across educational quintiles: Occupations requiring medium education consist of most routine tasks and occupations in educational quintile 1 show relatively low routine task intensity on average. This would imply that we also find polarization in the educational structure. But as we know, this does not correspond with our empirical evidence: Occupations with low education are in fact declining the most and thereby certainly declining less than occupations with medium education. Thus, routine task

[5] Goos et al. (2014) also use a version of this variable with ISCO88-coding, but only provide data for 21 of 28 2-digit occupational groups.

[6] To apply this measure to European labor markets, I map the variable of Autor and Dorn (2013) into the ISCO-scheme. Thanks to the level of detail in the original data, I am able to obtain values for occupations on the ISCO88 4-digit level. These values are aggregated into 3-digit occupational categories, before they are matched with the original ELFS individual level data from 1998 until 2010. Next, I estimate mean values of 2-digit occupations separated by country and year, each weighted by their unique composition of 3-digit occupations. To obtain data for the sample period after 2010, I further map the 4-digit ISCO88 values into the 3-digit ISCO88 scheme. These values are then also matched with the ELFS data and used to estimate weighted means for each 2-digit occupation.

intensity as measured by Autor and Dorn (2013) is unable to explain patterns of occupational change in the educational structure all by itself.
One might object to this conclusion by pointing out that it is merely based on average patterns. Possibly, the tested variable could accurately predict an upgrading of the educational structure in many cases, if the countries were examined separately. As I find however, this is not the case at all. The variable created by Autor and Dorn consistently predicts polarizing patterns for virtually all countries, both for wages and education (see appendix).

Nevertheless, since the routine content of occupations is a topic of ongoing debate, I also test three alternative measures that were created more recently. One of them is a variable created by Fernández-Macías and Hurley (2017). It is based on data from the European Working Conditions Survey and measures the routine content of all ISCO88 occupations on the 2-digit level. Since the 2-digit level is not detailed enough to map values into the newer ISCO08 scheme, I can only use this variable for the period between 1998 and 2010. The second variable however is created by Marcolin et al. (2016) and is available at the ISCO08 3-digit level. Thus, I am able to convert values into the ISCO88 2-digit scheme, thereby covering the whole sample period from 1998 until 2015. This variable also directly measures the routine content of occupations and is based on data from the OECD survey of adult skills.

The third variable however requires a little more explanation, since it is technically not a measurement of routine task intensity. In fact, it is based on the insight that routine tasks are not the only tasks anymore that machines can emulate. As Frey and Osborne (2017) claim, machines have learnt to perform many non-routine tasks due to recent technological progress. One prominent example are autonomous vehicles: Originally, Levy and Murnane (2004) claimed that car drivers cannot be replaced by machines because it would be “hard to imagine discovering the set of rules that can replicate a driver’s behaviour”. But this is exactly what happened: Already in 2010, Google introduced their first fully autonomous vehicles (Brynjolfsson and McAfee 2012). Since then, technology for autonomous cars has been further developed by various companies, and now cars are even legally allowed to drive autonomously on public roads in certain places. And this is just one of many examples for technological progress in emulating non-routine tasks. Therefore, Frey and Osborne (2017) conclude that it would be more efficient to define the remaining bottlenecks of current technology than its countless existing capabilities. According to them, machines are still lacking the skills to compete with real people in tasks requiring perception and manipulation, creative intelligence, or social intelligence.

Based on these insights, Frey and Osborne (2017) create a new measure of susceptibility to computerization. They analyze the task content of more than 700 occupations and determine the probability with which each occupation can be computerized[7]. I believe we can use this variable as an alternative measurement of routine task intensity, because it is also a task-based measurement that wants to explain why certain occupations can be replaced by machines and others can't. The only difference is that Frey and Osborne provide a more detailed (and probably more updated) description of the tasks that can actually be emulated by machines. Therefore, it should not be excluded from other variables that measure susceptibility to automation.

Figure 10: Mean Routine Task Intensity across Educational Quintiles, Alternative Measures, 1998

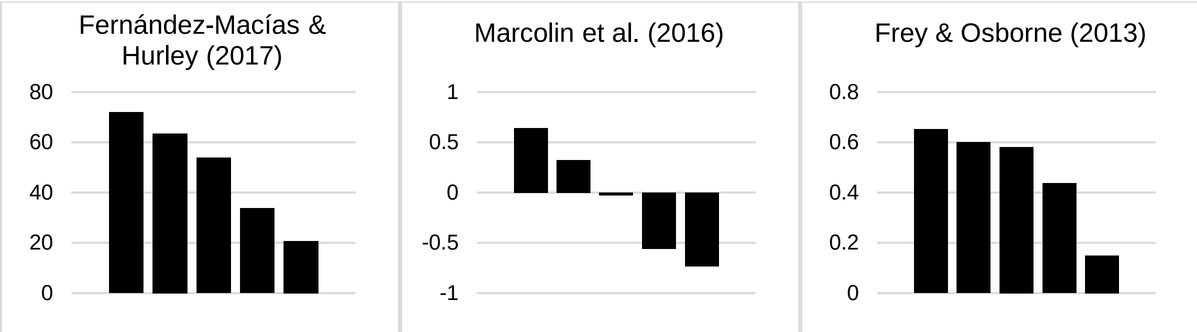
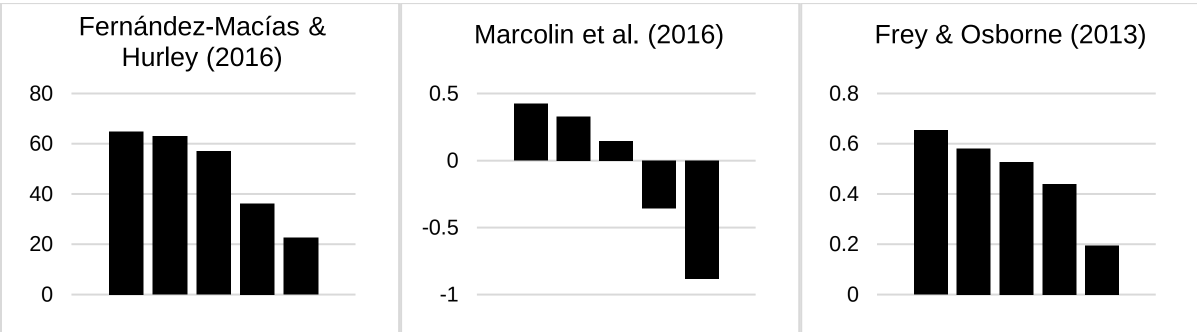


Figure 11: Mean Routine Task Intensity across Wage Quintiles, Alternative Measures, 1998



Interestingly, all three alternative measures imply the same patterns of change across wage and educational quintiles. They all clearly show that occupations with the highest educational requirements and with the highest wages are least susceptible to automation. On the other hand, occupations with the lowest educational requirements and lowest wages are most susceptible to automation according to all three variables.

[7] Occupations are defined by Frey & Osborne according to the US OCC-SOC scheme and must therefore be mapped into the ISCO scheme. I apply the same procedure as with the variable provided by Autor & Dorn (see footnote 6)

Regarding education, this matches our findings from before: The empirical data in fact shows that occupations with low education decline the most and those with high education expand the most. But in reference to the wage structure, our three alternative measures are less successful in predicting actual patterns of occupational change. As depicted in figure 11, they all claim that occupations with low wages are most susceptible to automation and should therefore decline the most. Occupations with medium wages are assumed to be considerably less susceptible and occupations with high wages to be the least susceptible. This however is clearly not the case in most European countries in our sample: Most often, wage quintile 3 displays more decline than all others. Therefore, apparently none of these alternative variables are able to explain why occupations with medium wages are declining more than those with low wages. And again, this problem is not caused by cross-country variation: All three variables predict upgrading of national wage structures very consistently across countries (see appendix).

Thus, we seem unable to find a generally valid explanation why certain occupations are declining faster than others. Each tested measure of susceptibility to automation can explain either upgrading in education or polarization in wages, but never both. This leaves us with only two possible options: First, we could assume that all our tested variables are inaccurate measures, and we just have to keep on searching for the real characteristics that make occupations susceptible to automation. Or, second, we could acknowledge that occupational change is not fully explicable by measuring how easily certain tasks can be automated.

Although the first option can never be ruled out completely, it seems rather unlikely. Many of the newer measurements (as those displayed in figures 10 and 11) are certainly well founded in technological knowledge and seem to represent actual capabilities of recent technology. In many examples, they can coherently explain what makes an occupation easy or hard to emulate for computers. Accordingly, these measures all display significant correlations with observed occupational change in regression analyses (see table 6). Their plausibility is further supported by the fact that these newer measures all come to the same conclusion: Occupations with low wages and low educational requirements are most susceptible to automation. Thus, it seems very likely that our measures are in fact valid, but that there are other influences as well. This becomes even more clear if we realize what our variables actually represent: They measure nothing else but pure technical feasibility. And, as I am going to show in the following chapters, there are good reasons why we should not succumb to technological determinism when talking about occupational change.

7. A New Theoretical Framework

Even though most researchers see technological progress as the main cause of occupational change, it is apparently impossible to fully explain patterns of occupational change without accounting for other influences as well. Therefore, I am going to present several alternative influences on occupational change in the following sections. Before I start however, it is important to mention that most of the presented effects are not part of the academic discourse on occupational change yet. The aim of this chapter is therefore merely to make a few suggestions for broadening the discourse. I neither claim that any of the proposed effects are in fact observable, nor that my list of potential effects is exhaustive. However, I strongly emphasize that technological determinism, as it is often practiced in the academic debate until now, is not a viable option in any case. Even if all our following propositions turn out to be empirically wrong, there must be other influences on occupational change than pure technical feasibility.

Costs and Benefits

The first explanation, that I want to put forward, is based on the assumption that wage structures themselves are an important factor that we must consider when analyzing occupational change. It is necessary to start with this effect, because it clearly demonstrates the necessity to revise current theory and shows how it could be expanded meaningfully. My main argument is that SBTC and RBTC both ignore basic economic theory if they only consider potential costs, but not potential benefits of replacing a human worker with a machine. As we will see in following sections, many effects that are already discussed in the literature can only be fully understood if benefits are considered as well. Therefore, I want to provide a suitable theoretical framework first, before we can talk about these other effects properly.

It is certainly indisputable that occupational change is fully dependent on decisions made by employers. Each employer, who has work to be done, can choose between hiring a person or buying a machine to take care of the work. As in each economic decision, the employer should carefully weigh up potential costs and benefits of each option, if he wants to make a reasonable decision. So far however, we have only discussed the costs of replacing a worker: the price of the machine. We simply assumed that occupations decline more if their tasks are easier to emulate for a machine, thus making the required machine cheaper (Autor et al. 2003). Clearly, this is a very important factor and maybe even the crucial factor in most cases. If, for example, there is no machine on the market that is able to fulfil a complex task, it is usually cheaper to hire a worker than to develop a new machine. Similarly, it is probably more efficient most of the time to buy a machine for tasks that are easily emulated. However, this view is obviously oversimplified, since potential benefits are completely ignored. And, as I argue, these benefits are sometimes highly important for employers' decisions.

Speaking in favor of machines, at least two relevant benefits must be considered. First, wage costs can be saved if a machine is bought instead of hiring a person. Naturally, the size of this benefit depends on the wage that a worker in the required position would earn. Saving high wages is a greater benefit than saving low wages[8]. The same idea obviously also applies to situations where employees are hired already. For example, we could picture an employer whose company has to become more efficient if it wants to compete on the market. Thus, the employer decides that he wants to cut costs by replacing one of the workers with a machine. All workers in his company earn different wages but are equally replaceable, i.e. machines to replace them all cost the same. In this case, the employer would probably fire the employee with the highest wage, since he can save most money by doing so.

As this example demonstrates, the benefit of saving wages acts as an incentive for employers to rather replace high wage earners than low wage earners. Admittedly, situations in reality are seldom as clear as in the given example. Usually, machines that can replace high wage earners are more expensive than machines to replace low wage earners (see figure 11 above). For example, developing artificial intelligence to replace a manager is certainly more expensive than buying software for bookkeeping. Thus, the decision becomes more complicated: If an employer replaces a high wage earner, he pays more for the machine. But if he buys a cheaper machine, he saves less on wages. Higher benefits are therefore often accompanied by higher costs.

Nevertheless, it's not possible to predicts employers' decisions by only looking at the cost side and ignoring the potential benefits of saving wages. Always, both sides must be considered: In some cases, benefits might be unusually high compared to the costs, and in other cases, the costs might be so high that benefits don't matter at all. In fact, this could explain the observed patterns of labor market polarization regarding wages. As seen in figure 11, susceptibility to automation is only decreasing slowly from wage quintile 1 to quintile 3, compared to the clear drop in susceptibility of quintiles 4 and 5. Thus, machines to replace any workers in quintiles 1-3 might cost almost the same. If this is true, then costs are not the

[8] Obviously, wages can also be interpreted as costs of hiring a human worker. However, additional costs of option 1 can always be translated into respective benefits of option 2. Since my focus lies on the option that includes automation, it seems appropriate to choose this perspective.

relevant factor here. Instead, potential benefits decide which occupations are replaced by machines and which ones are not. And, since it is more profitable to save medium wages than low wages, occupations in quintile 3 are more often replaced than those in quintile 1. In short: Tasks of occupations in wage quintile 3 are not much harder to emulate than tasks in quintile 1, but more money can be saved on wages here.

One might ask now why occupations in wage quintiles 4 and 5 are not replaced more often, even though much more money could be saved on wages here. The answer is given by the steep drop in susceptibility to automation between quintiles 3 and 4. Apparently, tasks of high wage occupations are considerably harder to emulate than others, making machines much more expensive. In this case, the high costs of machines are not outweighed by the higher benefits anymore. Thus, costs seem to be the only dominating factor at the top of the wage structure, while benefits of saving wages is more important in wage quintiles 1-3.

Productivity Gains

Also building on the economic rationality of a cost-benefit analysis is my next proposition: I argue that the benefits of replacing a human worker are not only defined by saved wages, but also by potential gains in productivity.

So far, we have assumed that machines and human workers are equally productive. One machine can replace exactly one human worker in these models. Thus, if the machine's acquisition and operation costs are cheaper than the wage of the worker, the worker will be replaced by the machine. By doing this, the company can save wage costs and still receive the same amount of work as before. But if the wage of the worker is cheaper than the acquisition and operation costs of the machine, the worker can most likely keep his job.

This simple model is certainly not wrong, and it is well capable of demonstrating the general importance of costs and benefits. However, it ignores that machines can be much more productive in certain tasks than people. In industrial food production, for example, one machine can replace nearly a whole factory full of people. Naturally, these machines are usually quite expensive. Therefore, the owner of the company must wisely weigh up the costs of the machine against the total wage costs of all workers. It is plausible however that in some cases, the machine will still be the more efficient option and therefore the company owner will replace all workers with only one machine. This clearly demonstrates the importance of productivity: A machine might be much more expensive than one worker's wage, but the machine's higher productivity enables it to replace more than one worker at the same time. Therefore, the wages of all workers, that a machine can replace, must be added up before weighing them against the costs of the machine. In general, the relative costs of the machine decrease with increasing productivity, thus making the machine a more attractive option. If, for example, a machine can not only replace one worker at a time, but produce as fast as hundred workers combined, it becomes more likely that the machine will be used.

It is important to note that productivity is not depending on how hard tasks are to emulate for machines. There might be several tasks that are very hard to teach to a machine, but once the machine has learned them, it can easily do them much faster than a person. The task of recognizing spoken language and giving appropriate reactions, for example, is certainly not easy to emulate, since there are countless combinations of words, which makes it hard to define universally valid rules for this task. In addition, the meaning of sentences often depends on context which is not explicitly mentioned, thereby making it even harder for machines to have a conversation with a person. Thus, reliable spoken language technology is currently still under development. Nevertheless, digital assistants like Apple's Siri, Microsoft's Cortana, Amazon's Alexa or the Google Assistant are first examples of useful applications of this technology. And they are all making fast progress, as tests demonstrate (Munster and Thompson 2018). In 2018, Google even introduced a new feature to its assistant that allows it to make restaurant reservations over the phone autonomously. And if we assume that technology for speech recognition is developing further, we can easily imagine that it will start to replace human workers soon. Call center agents, for example, might become obsolete if all questions can be answered by machines. And in this case, the potential productivity gains are immense: One computer can easily replace hundreds of call center agents, since it can handle innumerable calls at the same time. Only limited computational power is required and there is no need for physical presence at any point during the task. Thus, one computer can sometimes easily replace a lot of people, even though it was very hard to find the rules describing the required task. Or, in other words: Low routine task intensity can occur together with high potential productivity gains.

Naturally, the opposite case is equally plausible: High routine task intensity can occur together with low potential productivity gains. This could be true for supermarket cashiers, for example: Their work is rather monotonous and rules for their tasks are already well defined. In fact, machines already started to replace human cashiers in several countries. As we see, machines are easily capable of doing the tasks of cashiers. Nevertheless, one machine can only replace one worker in this case. Obviously, it is not possible for two customers to be served at the same time by one machine due to physical limitations. Multiple customers can only be served at the same time, if multiple machines are deployed[9]. Thus, there are only low potential productivity gains in replacing a cashier, even though the required tasks are easily emulated.

This argument could be of special importance with regards to machine operators, craft workers and office clerks which all show most decline on average. In all these occupations, machines can drastically increase efficiency: A computer can easily operate all machines in a factory simultaneously and without mistakes, a machine can produce tables a great many times faster than a craftsman, and a computer program can do the year's work of a bookkeeper in a single instant. On the other hand, efficiency is not increasing by much if we let robots clean our streets, for example, since a cleaning robot can still only clean one spot at a time and takes time to move around. This might partly explain why elementary occupations are not declining as much as we would expect based on their high routine task intensity.

Preference for Interpersonal Contact

In my next proposition, I want to part from economic rationality and argue that we must also take non-economic preferences into account when talking about occupational change. The argument is based on the assumption that people often value interpersonal contact as an end in itself, and not just as a pure means to pursue other interests (Levy and Murnane 1996). This seems intuitively plausible and can probably be understood by most somehow sociable people. In addition, literature on life satisfaction supports this assumption by frequently referring to interpersonal contact as an important influence on people's wellbeing (McGrath 2012).

If interpersonal contact is indeed valued positively, this implies that people often prefer interactions with other people to interactions with machines. Of course, I must admit that people sometimes prefer machines if they provide a better or more efficient service. Buying a train ticket, for example, is much more efficient on a smartphone than at a ticket counter with a long queue. Therefore, many people prefer buying tickets on smartphones. But if a person and a machine provide the same service with equal efficiency, we would assume that many people would choose to interact with the person, simply because it is a person.

---

[9] Multiple customers can also be served at the same time if one machine offers multiple interfaces. But in the case of cashier machines, this is basically the same thing as having two machines.

This affects the cost-benefit analysis of employers in two ways: First, employers themselves might prefer working with real people to working with robots. Going to office everyday can be much more pleasurable, if there are some colleagues that you can talk to from time to time. Talking to robots is certainly an option, too, but it seems rather unsatisfying eventually. Second, employers must also consider the preferences of their customers: If they are rather served by a person than by a machine, the employer is wise to hire a person instead of buying a machine. But if he makes the wrong choice, many customers will probably avoid his company and switch to other companies where they are served by real people. Thus, the preference for interpersonal contact must be weighed among the benefits of hiring a person, or among the costs of buying a machine respectively. In consequence, some occupations that include interpersonal contact might not be replaced by machines as quickly as would be technically feasible.

This is of special importance for service occupations, since they probably include most interpersonal contact: Although machines could provide many services in similar quality, most people probably feel more comfortable if they are served by real persons. Nursing robots, for example, could possibly take over many tasks of health care assistants (and already do so in Japan), but people apparently value personal contact as an end in itself and are rather taken care of by real people. Or another example: Barkeepers could quite easily be replaced by vending machines in theory. Mixing cocktails might be a little more complex than brewing coffee (which machines already do) but the concept is the same: Take certain ingredients and then follow a clearly defined recipe. But a barkeeper is not only there to serve drinks, but also to provide an opportunity for pleasant interpersonal contact. He can keep up some humorous small-talk while preparing drinks, for instance, and thus make the whole experience a more pleasant one. This could help explain why service occupations are expanding their employment share in most countries, even though machines would be capable of replacing at least some of them.

Offshoring & International Trade

Another alternative influence on occupational change, that I want to present here, is offshoring of jobs. Besides the effect of technological feasibility, this one is certainly the most frequently discussed in the academic and the public discourse. It was made prominent by Alan Blinder (2009) who introduced a measurement of offshorability that is used in many academic articles ever since. His message is simple: Certain occupations don’t require physical proximity to deliver their work. Therefore, these occupations can be offshored to countries with cheaper wages, thereby delivering the same work for less money. According to Blinder, computer programmers, telemarketers, and computer system analysts are among the occupations that could be offshored most easily, since their work does not require physical proximity at all. On the other side of the scale, he lists occupations such as sales agents, photographers, and mail carriers, since they can't do any work without immediate physical proximity. It would obviously be absurd to assume that someone can take photos of a wedding ceremony that is happening in another country or even just another city.

Clearly, this affects the patterns of occupational change, since jobs that are offshored in large numbers tend to decline in domestic labor markets. Although many researchers mention this potential effect, only few actually consider it in their analysis of occupational change. To my knowledge, only Goos, Manning and Salomons (2014) estimate the effects of technology and offshoring in Europe in a combined model together with the effect of automation. However, they only found that the effect of offshoring was not shown significant in all combined models. Nevertheless, I also want to examine this effect by using my own sample. Therefore, I take the original variable of Blinder (2009) and once more map in into the ISCO scheme.[10]

Figure 12: Mean Offshorability (Blinder 2009) across Educational and Wages Quintiles

As can be seen in figure 12, average offshorability is lowest in quintile 1 of both the educational and the wage structure. Therefore, jobs with low wages and low educational requirements are relatively safe from being offshored. But offshorability increases with rising education and rising wages. In education, the peak is reached in quintile 4, before offshorability declines again in quintile 5. In wages however, offshorability increases up until quintile 5. Apparently, offshorability does not correspond to our observed patterns of occupational change: In the educational structure, offshorability would predict the contrary of what we observed. In the wage structure, a prediction based on offshorability would also be contradictory, since we don't observe a decline of jobs in quintiles 4 and 5.

[10] I apply the same procedure as with the variable provided by Autor & Dorn (see footnote 6).

The only thing that offshorability might actually explain is why jobs in the middle of the wage structure are declining faster than those at the bottom: They are clearly more offshorable. But since there is no correspondence between offshorability and our observations in all other areas, it is questionable whether offshorability really makes a difference. To answer this question, I estimate several linear regression models, using occupations' change in national employment share as dependent variable[11]. By testing different measures of susceptibility to automation combined with offshorability, we should be able to isolate the effect of offshoring. Results are displayed in table 6.

Table 6: Linear Regression Models Estimating Effects of Offshoring on Occupations' Change in Employment Share

Measure of Susceptibility to Automation	Education	Autor & Dorn (2013)	Fernández-Macías & Hurley (2016)	Marcolin et al. (2016)	Frey & Osborne (2013)	None
Susceptibility to Automation	0.121***	-0.049***	-0.006***	-0.082***	-0.375***	-
Offshorability	-0.024	0.038*	-0.010	-0.016	0.005	-0.003
Observations	2,873	2,873	1,950	2,873	2,873	2,873
Adj. R^2	0.038	0.006	0.040	0.011	0.023	0.0000

*** p<0.01, ** p<0.05, * p<0.1

Apparently, my results confirm the findings of Goos, Manning and Salomons (2014): Offshoring does not correlate significantly with an occupation's decline or growth, when controlled for the effect of automation. In fact, it doesn't even correlate with occupational change in a stand-alone model. Only when combined with the variable created by Autor and Dorn, the effect of offshorability is slightly significant. Thus, assuming that Blinder's variable is a valid measure of the concept, offshorability does not seem to be an important influence on occupational change in Europe.

On the positive side, we note that all tested measures for susceptibility to automation display high levels of significance and point in the direction that we would expect. Nevertheless, explained overall variance is very low in all models, never reaching R2-values of more than 0.04. This underlines the claim that technological feasibility cannot be the only determinant of occupational change in Europe.

[11] Occupations are measured at the ISCO 2-digit level. The change in national employment share in each 4-year period 1998-2002, 2002-2006, 2006-2010, and 2011-2015 is counted as an observation for each occupation. Robust standard errors are used to control for intra-group correlation since each occupation is measured repeatedly within a country.

Before moving on to the next chapter, I want to mention another effect that is closely related to offshoring: international trade. This approach claims that domestic production of certain goods decreases if these goods are imported in large numbers. Therefore, less workers are needed to produce these goods and employment in affected occupations declines. The similarity to offshoring is obvious: In both cases, jobs are moved from one country to another, where foreign workers produce the same goods that were produced by domestic workers before. The difference between the two approaches is mainly analytical: While Blinder focuses on specific tasks that make occupations offshorable, other researchers use exposure to import competition of economic sectors as their explanatory variable. Thus, they expect employment to decline in occupations that are affected by import competition. By using this approach, they usually find evidence for job decline, even when controlling for the effect of technological replacement. However, to my knowledge, existing studies only examine developments in the USA (Acemoglu et al. 2016; Autor, Dorn, and Hanson 2013; Autor et al. 2015). Therefore, this would certainly be an interesting approach to apply on European labor markets as well in future research. Within the scope of this thesis however, this project would exceed my possibilities.

8. Country-Specific Determinants

In the previous chapter, I have presented several factors that potentially shape patterns of occupational change in addition to pure technical feasibility. Together, these factors might be able to explain general trends in the occupational structure. However, the previous chapter is unable to explain differences between countries: The presented effects only describe why certain occupations are affected by automation (or offshoring) but ignore country-specific circumstances. This is clearly a shortcoming of my analyses so far, since there is considerable variation in patterns of occupational change across countries (see chapters 4 and 5). For this reason, I want to present possible causes of these country-differences in this chapter.

Original Composition of Labor Markets

If we want to explain national differences in patterns of occupational change, we certainly have to consider the various compositions of national labor markets in the beginning of our sample period. The reason is obvious: If labor markets are composed of different occupations, they probably develop differently. If, for example, certain occupations are virtually non-existent in a country, then there is not much potential for decline in these occupations.

According to Oesch (2013:51), this is of special relevance regarding the decline of agricultural occupations. First, he observes that employment in agriculture is generally showing rapid decline due to automation. And since agricultural occupations are usually among the ones with least educational requirements and lowest wages, Oesch argues that potential for decline in bottom quintiles is depending on the national share of employment in agricultural occupations. Thus, if agricultural occupations account for a large share of employment, the potential for decline in bottom quintiles is higher than if bottom quintiles are almost entirely composed of other occupations that decline more slowly, if at all.
Obviously, the decline of bottom quintiles is crucial for defining the pattern of occupational change: In fact, it makes the difference between upgrading and polarization. If bottom quintiles decline strongly, upgrading patterns become more likely, and if bottom quintiles decline slowly or even grow, polarized patterns are the consequence.

As Oesch (2013:51) observes, there are large differences in agricultural employment between countries, thus implying significant differences in potential for decline in bottom quintiles. This is also true for our sample: In 1998, more than 17% of all employment fell on agricultural occupations in countries such as Poland or Greece, while in many countries, agricultural occupations only accounted for little more than 1% (see Appendix). Thus, we would expect that countries with more agricultural employment are more likely to display upgrading patterns than others.

To test this hypothesis, I analyze the original compositions of labor markets at the beginning of our sample period in 1998. To do so, I first divide all countries into groups according to their pattern of occupational change. Each country is categorized twice: Once for its pattern of change regarding the educational structure and once for its pattern regarding the wage structure. The categorization consist of three patterns, as can be seen in figures 3 and 5: upgrading, polarized upgrading, and polarization. I then compute the average composition of each quintile separately for these six groups of countries.

Figure 13: Mean Composition of Educational Quintiles 1998 across Patterns of Occupational Change

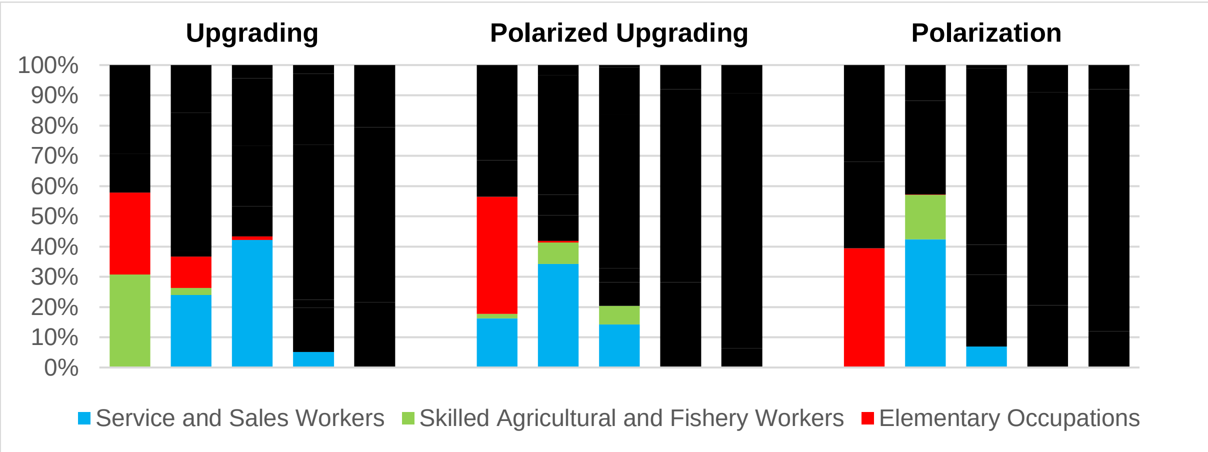
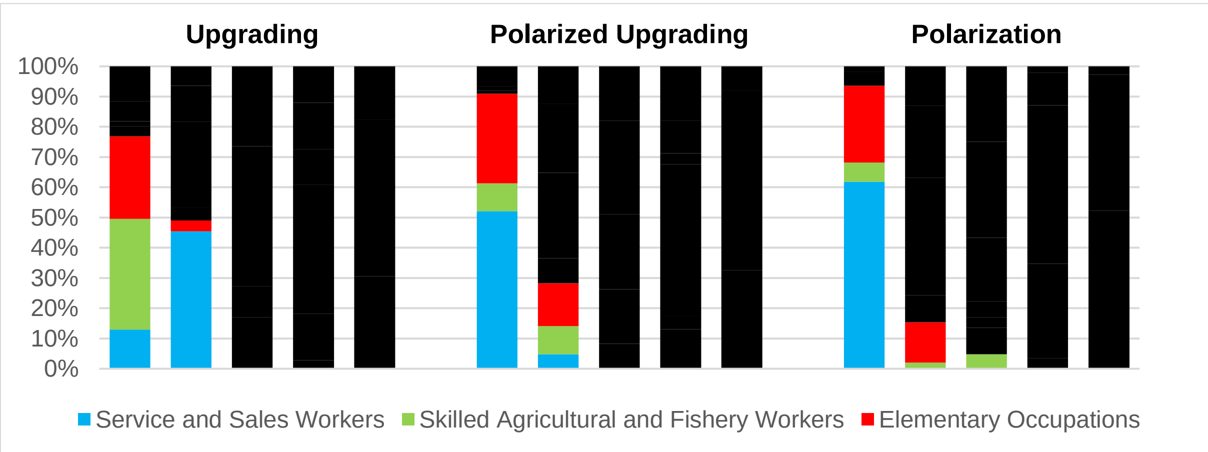


Figure 14: Mean Composition of Wage Quintiles 1998 across Patterns of Occupational Change



As can be seen in figures 13 and 14, the original employment share of agricultural occupations is considerably larger in labor markets that are displaying upgrading patterns in the following years. This applies to both the educational and the wage structure. In countries with little agricultural employment however, the share of service and elementary occupations in quintile 1 becomes significantly larger. And since service jobs are growing and elementary jobs are remaining constant on average, quintile 1 is less likely to decline in these countries. Thus, little initial employment in agriculture is associated with polarized patterns of occupational change.

Of course, this correlation might only be a coincidence, and other occupational groups might in fact cause the change within quintiles that leads to diverging patterns of occupational change. To account for this problem, I also calculate the average composition of change across quintiles. In chapter 6, I have already done this for average change in the educational and the wage structure. Now, I want to break down these general trends into more precise descriptions of change within the six groups described above.

Figure 15: Mean Composition of Change in Educational Quintiles across Patterns of Occupational Change

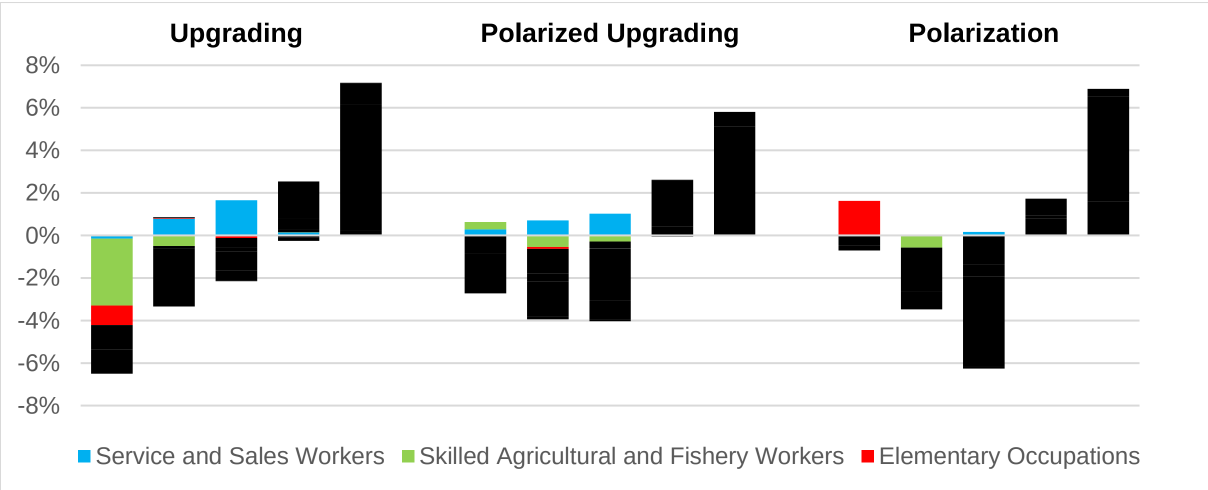
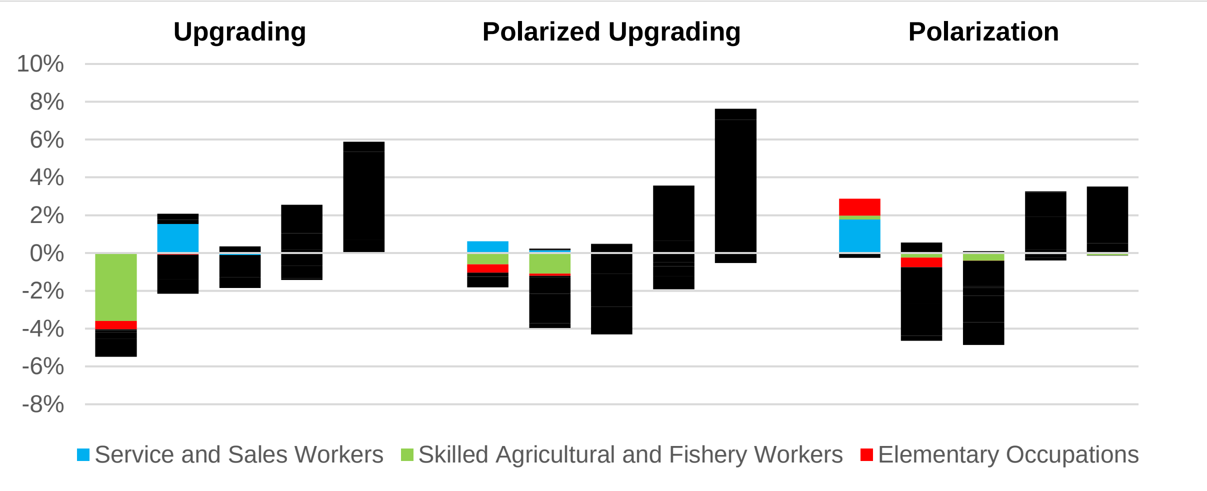


Figure 16: Mean Composition of Change in Wage Quintiles across Patterns of Occupational Change



As we see in figures 15 and 16, agricultural occupations are largely responsible for the decline in quintile 1 in the educational and in the wage structure. Elementary and service occupations however have very little influence on change in bottom quintiles of upgrading labor markets. But this is changing if we look at polarizing patterns: Here, the decline of agricultural occupations is lacking almost completely, and is replaced by the stability of elementary occupations and the growth of service occupations in quintile 1. Thus, quintile 1 is showing less decline or, depending on growth of elementary and service occupations, even overall growth. The composition of quintiles therefore corresponds with the observed change within quintiles: If a large employment share falls on agricultural occupations, bottom quintiles are declining faster, thus making an upgrading pattern more likely.

Institutional Wage Setting

National institutions are often assumed to set a certain wage floor, thus controlling how low wages can fall within a country. This clearly affects patterns of occupational change, if we consider not only costs, but also benefits: If wages in certain occupations are very low, then potential benefits of replacing these workers are equally low. In these cases, human labor might be so cheap that it’s not worth replacing them with machines. Thus, institutions are altering the benefits of replacing a human worker with a machine by manipulating the wage structure.

Therefore, it is often assumed that countries with relatively low wage floors display less decline in low wage occupations than others. If labor is very cheap, there is little reason not to hire it, even though a machine could easily replace it. On the other hand, higher wage floors might just make the difference and make it more profitable to use machines instead of human labor. In this case, low wage occupations should decline faster. In consequence, countries with low wage floors are assumed to be more prone to wage polarization than countries with higher wage floors (Oesch 2013).

To examine the effect of wage setting however, we first need to understand how institutions can influence the wage structure. Only this way can we link single institutions with occupational change. According to the literature, institutions mostly affect occupations at the bottom of the wage structure (Fernández-Macías 2012; Oesch 2013). To protect laborers, most countries define a series of minimal standards in different domains, thereby defining characteristics of jobs with low standards more strongly than jobs with standards that are high already. The most obvious example is certainly minimum wages: By setting a minimum wage, a country defines a precise wage floor and thereby decides how much people at the bottom of the wage structure should earn. Someone who earned less than minimum wage before will necessarily earn more after the introduction of the minimum wage. However, everyone who earned more than minimum wage before already, is most likely not affected by its introduction. Possibly, some incomes close to the minimum would rise as well in order to maintain the occupational stratification, but higher incomes don’t need to adjust.

By setting a relatively high minimum wage, a country therefore causes higher incentives to replace human labor in low wage jobs than there would be with a low minimum wage or none at all (Hornstein, Krusell, and Violante 2004; Oesch 2013). But legal minimum wages are not the only influence on a country’s wage floor. Other, less obvious effects also play their part: For example, collective bargaining through labor unions might set wage floors that differ from legal minimum wages in certain occupations. In fact, several countries in Europe don’t even have any legal minimum wage and regulate all wages through collective bargaining (e.g. Switzerland, Sweden, Norway). Thus, we might expect to find higher wage floors in countries where unions are more powerful (Hornstein et al. 2004). This is usually measured by rates of collective bargaining coverage within a country (Oesch 2013).

Another potential effect is also regularly discussed in the literature, although its influence on setting wage floors is only of indirect nature: Unemployment benefits are thought to set an informal wage floor, since they offer a certain wage substitution without having to work for it. If, for example, the benefits amount 50% of the previous wage, it always pays off to accept a job with a higher wage than these 50%. But if the benefits are more generous and amount 80%, it is unlikely that someone will accept a job with only 60% of the previous wage. Thus, people are less willing to accept low wages if unemployment benefits are more generous. In contrast, the number of persons employed in low wage occupations is expected to rise more if unemployment benefits are low (Fernández-Macías 2012; Hornstein et al. 2004).

Considering the low number of studies that examine occupational change in multiple European countries, it is no surprise that the number of those testing the influence of institutions is even lower. In fact, no results about the link between single institutions and occupational change have been published yet to my knowledge. Nevertheless, some authors treat the topic with different degrees of approximations. Rather vague, for example, is the conclusion of Hornstein et al. (2004) who find that there is a stronger tendency towards upgrading in Europe than in the USA, probably due to institutional differences. A little more detailed however are the observations of Fernandez-Macias (2012) who compares the patterns of occupational change across different institutional clusters within Europe. First, he finds that the top wage quintiles grow consistently across countries, but the development of bottom quintiles differs considerably. This supports the theoretical claim that institutional differences mainly affect low wage occupations. Further, he associates a tendency towards polarization with Continental Europa, and a tendency towards upgrading with Scandinavia. To some extent, this is also confirmed by my data (see figure 5). He explains this discrepancy with the different institutional settings of these clusters: In Scandinavia, wage floors are generally high due to strong unions and generous benefits, but in Continental Europe, the opposite is true. Finally, the findings of Oesch and Menes (2011) or Oesch (2013) are most detailed, but only include four or five countries each. They analyze the effect of institutions by examining wage floors, measured as the ratio between median wages in quintile 1 and overall median wages. Thus, rather than the source of the effect, they measure wage inequality as its intermediary. This seems sensible, since institutions only affect growth of low wage jobs by manipulating wage floors, according to theory. In both studies, the authors observe that high income inequality is connected with less decline in low wage quintiles. However, not all occupations are affected equally. It seems that, apparently, decline of service occupations is by far most dependent on wage floors: If wages in quintile 1 are relatively high, they decline just like other occupations. But if wages in quintile 1 are relatively low, service jobs even grow in some countries, thus leading to polarization. This corresponds to our finding that service occupations are in general the only group in low wage quintiles which display significant growth (see figure 7). Oesch (2013) explains this finding by referring to the elasticity of service labor demand: If hiring a cleaning worker is rather expensive measured by one's own salary, people simply clean themselves. But if wages of cleaning workers are relatively cheap compared to others, demand for their services rises strongly.

To test the effects of institutional wage setting independently, I analyze the change in employment share of relevant occupations under different institutional circumstances. As mentioned above, institutions are most likely to influence growth at the bottom of the wage structure. Therefore, occupations in wage quintile 1 are certainly a relevant group that I must consider in my analysis. Further, I include service occupations as a separate group, based on the findings of Oesch and Menes (2010) or Oesch (2013)[12]. All occupations are measured at the ISCO 2-digit level. The change in employment share in each 4-year period 1998-2002, 2002-2006, 2006-2010, and 2011-2015 is counted as an observation for each occupation. Robust standard errors are used to control for intra-group correlation since each occupation is measured repeatedly within a country.

To compare institutions across countries, I use several variables provided by the OECD. I measure minimum wages, union power, and unemployment benefits as relevant institutions, but also income inequality as the crucial intermediary. The height of minimum wages, for one, is measured by the OECD in relative ratios to average wages of full-time workers in each country. Union power is measured as collective bargaining coverage, and unemployment benefits as mean net replacement rates. Lastly, I use the OECD's P50/P10 ratio to measure income inequality. It is perfectly suited for our purpose, since it measures the median of the lowest 10% in comparison to the overall median income in each country. However, this variable is only available starting with the year 2004 and even then, it is not completely available for all countries. Thus, I also use Gini-coefficients as a second measure of income inequality. Since OECD-data on Gini-coefficients is also incomplete, I use data from the World Income Inequality Database (WIID), thereby gaining almost fully complete data.

To match data on institutions with data on employment shares, I estimate mean values of all institutional variables for the same 4-year periods as mentioned above. To account for reversed causality however, I lag the institutional variables by one year before estimating means. Thus, change in employment share of occupation X in country Y between 2002 and 2006, for example, is matched with the means of our variables on institutions in country Y from 2002 until 2005. Unfortunately, data is still not perfectly complete for most measurements. Therefore, the number of available observations differs between variables. Nevertheless, data is at least 97.8% complete for all variables except for the P50/P10 ratio (59.5%).

[12] I have also tested for correlations with other quintiles and occupational groups, but none of them displayed any significant influence from institutions.

Table 7: Linear Regression Models Estimating Effects of Institutions on Occupations' Change in Employment Share

	Wage Quintile 1		Service and Sales Occupations	
	Model 1	Model 2	Model 1	Model 2
Minimum Wage	0.226	0.217*	0.184	-0.001
Collective Bargaining Coverage	-0.003	-0.002	0.000	-0.000
Unemployment Benefits	0.011*	0.010**	0.004	0.002
P50/P10 Ratio	-0.266	-	**0.473***	-
Gini-Coefficient	-	-0.006	-	**0.029****
n	316	532	153	239
Adj. R^2	0.013	0.012	0.007	0.013

*** p<0.01, ** p<0.05, * p<0.1

Using this data, I estimate the effect of institutions on change in employment share by employing several linear regression models. The results are displayed in table 7. Apparently, there seems to be no significant correlation between single institutions and change in employment share in any suspected way. Only unemployment benefits correlate significantly with wage quintile 1 in both models, but the direction of the correlation is contrary to what we would expect. While theory suggests that more generous unemployment benefits lead to less growth in low wage occupations, our data displays a contrary relationship.

Nevertheless, our data confirms the finding of Oesch and Menes (2010) or Oesch (2013) who claim that service occupations grow stronger in countries with higher income inequality. In both tested models, variables measuring income inequality display a significant positive correlation with service job growth. Thus, it seems plausible that demand for service workers is dependent on their relative level of income. In other words: If service wages are low compared to other wages, demand for service workers rises. But if service workers earn a wage closer to the median, people more often renounce their services and do the work themselves or let a machine do it[13]. It is surprising however that this correlation does not seem to have an effect on growth in wage quintile 1. Apparently, the weight of service jobs within wage quintile 1 is not strong enough to explain general tendencies of the whole quintile.

Thus, income inequality can (at least partly) explain why service jobs decline or expand, but not why wage quintile 1 declines or expands. We can explain this by considering the

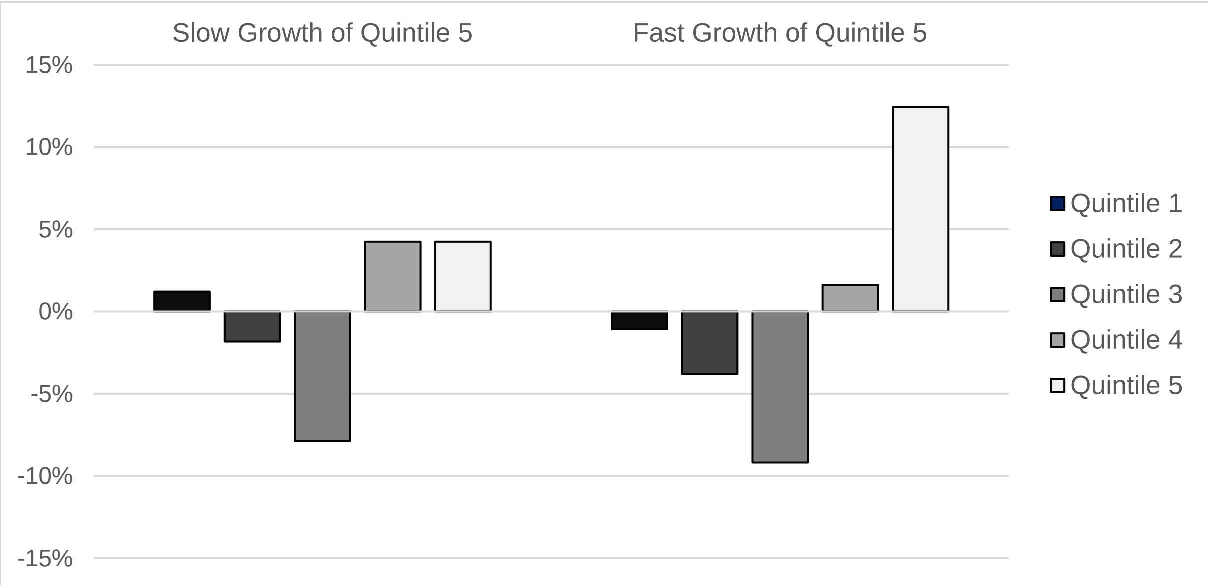
[13] This is the standard explanation as proposed by Oesch and Menes (2010) or Oesch (2013). However, we must note that causality could also be contrarious in this case: Polarization could cause higher income inequality. By lagging variables, I try to diminish this problem. However, the direction of causality cannot be determined definitely.

distribution of service jobs across wage quintiles 1 and 2: If all service occupations within a country rank in wage quintile 1, inequality probably has a significant effect on the growth of the whole quintile. But if all service occupations rank in wage quintile 2, inequality does not affect wage quintile 1, since no other occupational groups are comparably related to inequality like service jobs are.

Labor Supply

So far, we have mostly been speaking about explanations for patterns of change in occupations with low wages or low educational requirements. This is certainly not wrong, since patterns are much more diverse in these quintiles than in occupations with high wages and high educational requirements. In virtually all countries under examination, the latter display unanimous growth. Nevertheless, rates of growth in these occupations differ significantly between countries. This must also be considered a relevant influence on the whole pattern of occupational change, since it affects the relative growth of other occupations as well. In fact, the rate of growth in top quintiles can determine whether other quintiles are displayed as declining or expanding in comparison.

Figure 17: Hypothetical Patterns of Change in Employment Share, Depending on Quintile 5



To illustrate this fact, two hypothetical patterns of occupational change are depicted in figure 17. Absolute growth of occupations in quintiles 1-4 is exactly the same in the left pattern as in the right one. The only difference in absolute numbers is the growth of occupations in quintile 5: On the right side, they grow much faster than on the left side. This however causes drastic changes in the relative growth of quintile 1. On the left side, quintile 1 is relatively increasing, but on the right side, it is decreasing. Therefore, we observe a clear pattern of polarization on the left side and a pattern of polarized upgrading on the right side. The stronger growth of quintile 5 on the right side apparently outweighs all other growth and causes the whole pattern to change.

With this effect in mind, I want to examine whether there is an explanation for the varying growth rates of top quintiles. In the literature, only one explanation is discussed, but it is a very appealing one. As claimed by authors such as Goldin and Katz (2007) or Oesch (2013), the limiting factor at the top of the occupational structure is labor supply. Since occupations with high educational requirements or high wages are not very susceptible to automation but benefit from it, suitable workers are generally in high demand. But if demand is higher than supply, not all open positions can be filled and thus growth of these occupations is limited.

This effect can also be easily incorporated into our cost-benefit framework: If demand for suitable workers exceeds its supply, employers must compete against each other to hire the few available workers. Each employer must make the potential employee an offer that is more attractive than the other offers if he wants to have a chance of hiring the person. Obviously, making more attractive offers usually comes with higher costs, often in the form of higher wage offers. Therefore, workers in short supply often benefit from their scarcity, but employers are faced with additional wage costs. And according to our framework, these additional costs must be considered a reason for employers to buy machines instead of hiring workers. Thus, short supply of suitable workers leads to higher wage costs and finally to reduced employment in affected occupations.

What “suitable worker” means, is obvious in at least one case: Occupations with high educational requirements need sufficient numbers of highly educated workers. And since occupations with the highest wages are usually also among the occupations with highest educational requirements, the same probably applies for them, too. Among the occupational groups, we expect professionals to be most dependent on highly educated labor supply.

Highly educated workers can be obtained by countries in two ways: Either by training them in their own educational systems, or by immigration of workers that were trained abroad. Therefore, countries’ institutions are also important with regards to labor supply, since they shape educational systems and regulate migration. In my analysis however, I don’t measure the effects of these institutions separately, since they both have the same intermediary effect. Instead, I directly measure the educational attainments of a country’s population.

The general hypothesis is quite straightforward: Higher supply of highly educated workers allows for more expansion of jobs in wage quintile 5, educational quintile 5 and professional occupations. Although "high education" is easily defined by tertiary degrees, it is not quite clear how to define the relevant supply of workers. Thus, I include four different variables in my analysis[14]: First, I measure the share of people holding a tertiary degree by taking all people in working age (25-64) as reference. This is certainly the most accurate way to measure how many people with high education are available within a country. However, occupational change might be more dependent on educational attainments of young people, since they are the ones who enter labor markets for the first time and therefore supply labor markets with new workforce for newly created jobs. Thus, I include the share of people holding a tertiary degree between 25 and 34 as my second variable. Variables number three and four are also based on these two measurements but try to consider the dynamic nature of occupational change. One could argue that the share of people holding a tertiary degree only determines the employment share of certain occupations, but not the change in employment share. What really influences this change, is how many additional workers with high education enter labor markets. Thus, educational attainments should probably rather be measured dynamically as well by considering the rate of educational expansion. To do so, I include two variables that measure change in the share of people holding a tertiary degree. One of them is in reference to the population aged 25-64, the other one to the population aged 25-34.

To test these variables, I estimate their correlation with change in employment share of occupations that belong to the groups mentioned above. All occupations are measured at the ISCO 2-digit level. The change in employment share in each 4-year period 1998-2002, 2002-2006, 2006-2010, and 2011-2015 is counted as an observation for each occupation. Similarly, I use mean values over these 4-year periods for variables containing population shares but lag them by one year. The variables describing change in population shares however are summed up over the 4-year periods, thus containing the total growth in the share of people holding a tertiary degree. Naturally, this variable is also lagged by one year.

[14] All variables on educational attainments are provided by the OECD.

Table 8: Correlation Coefficients between Tertiary Education & Change in National Employment Share

	Educational Quintile 5	Wage Quintile 5	Professionals
Tertiary Education (25-64)	0.0602	0.0159	0.0474
Tertiary Education (25-34)	0.0861**	0.0456	0.0569
Δ Tertiary Education (25-64)	**0.2419*** **	**0.1929*** **	**0.2496*** **
Δ Tertiary Education (25-34)	**0.1460*** **	**0.1628*** **	**0.1431*** **

**** p<0.01, ** p<0.05, * p<0.1*
Correlation coefficients are estimated pairwise, thus including all available cases for each pair of variables.

As can be seen in table 8, absolute shares of tertiary education are not correlating significantly with occupational expansion in any of the tested groups. Educational expansion however shows considerably high levels of correlation in all tested groups. Thus, it seems like jobs at the top of the occupational structure grow faster if supply of highly educated workers is rising fast as well. Original levels of educational attainment in a population, on the other hand, are not important. Only change in educational levels is what affects occupational change.

However, not all correlations of educational expansion are equally strong. Among the two variables, the one including the whole working age population (25-64) is clearly superior to the one only regarding the population aged 25-34. In all groups, the correlation between educational expansion and occupational growth is considerably higher when using this variable. Thus, we can conclude that educational expansion in the whole population must be considered, not only in the young population.

Further, we can observe highest correlations between educational expansion and occupational growth in educational quintile 5 and in professional occupations. Wage quintile 5 seems to be less affected by educational expansion. This is no surprise: It is obvious that occupations with high educational requirements are most directly depending on highly educated workers. And, since growth in educational quintile 5 is almost exclusively based on growth in professional occupations, it is unsurprising that both groups are equally depending on educational expansion. On the other hand, even though high wage occupations also have high educational requirements in general, some of them are not among the highest. Thus, high wage occupations are less limited by insufficient supply of highly educated workers than the other two groups.

9. Occupational Change & Unemployment

In all previous chapters, I have discussed why labor markets display a pattern of general upgrading in some cases, but more polarized patterns in other cases. At different points, I have also mentioned potential implications of these developments for individual labor market participants. For example, upgrading of labor markets is usually seen as a chance for upward mobility, since many jobs are newly created at the top of the occupational structure and only those at the bottom are disappearing. Thus, many labor market participants are facing the opportunity to climb up the social ladder and get themselves a better job than before. But in a situation of labor market polarization, this is not the case. Here, employees in rapidly declining middle-class jobs are threatened by social descent, since not all of them might be able to find a better job. Thus, it is likely that some former members of the middle class will fall down into occupations with lower wages. These effects are rather undisputed and could also be shown in studies using individual level panel data (e.g. Cortes 2016).

However, some authors reject this view as an oversimplification, since only workers are considered who remain active parts of the labor market and are in fact able to find a new job. This excludes all people who don't succeed in finding a new job and therefore become unemployed or leave the labor market altogether. According to these authors, this is of special importance for upgrading labor markets: In them, the strong decline of occupations with low educational requirements might cause unemployment, even though many new jobs are created simultaneously. Supposedly, not all workers, that were formerly employed in these lowly educated occupations, can find another job, since they don't possess the necessary education. Many workers, who lost their job in this situation, will choose to be retrained in order to find a new job. But very likely, not all of them are able to do so. And for this group, risk of unemployment is very high, since not enough jobs with low educational requirements are available in a situation of occupational upgrading. Thus, jobs with low educational requirements might disappear faster than people with low education (Oesch 2013:127).

In a situation of polarizing labor markets, this seems less of a problem, since jobs with medium requirements are disappearing the most. Thus, some lucky people who lost their middle-class jobs can find a better one, and the rest can still settle for a job that requires less education than their former one. In polarizing labor markets, jobs with low requirements are not as hard to find as in a situation of upgrading, since they are not declining as fast (if at all). Therefore, labor market polarization is expected to cause less unemployment than upgrading (Hornstein et al. 2004; Spitz-Oener 2006).

This hypothesis is based on the work of Paul Krugman (1994) who claims that there is usually a trade-off between inequality and unemployment: If lowly educated workers are most at risk of becoming unemployed, a country can either choose to allow growth of low wage occupations, which leads to rising income inequality, or it can choose to pursue low inequality by keeping up a high wage floor, thus pushing some lowly educated workers out of the labor market and into unemployment. By replacing inequality with polarization, several authors used Krugman's theory to formulate the hypothesis described above. This seems plausible, since labor market polarization is closely linked to rising inequality. However, empirical evidence in support of Krugman's original trade-off is rather scarce (Glyn 2001; Nickell and Bell 1996). Therefore, it is not clear whether labor market polarization really allows for lower unemployment rates than upgrading labor markets.

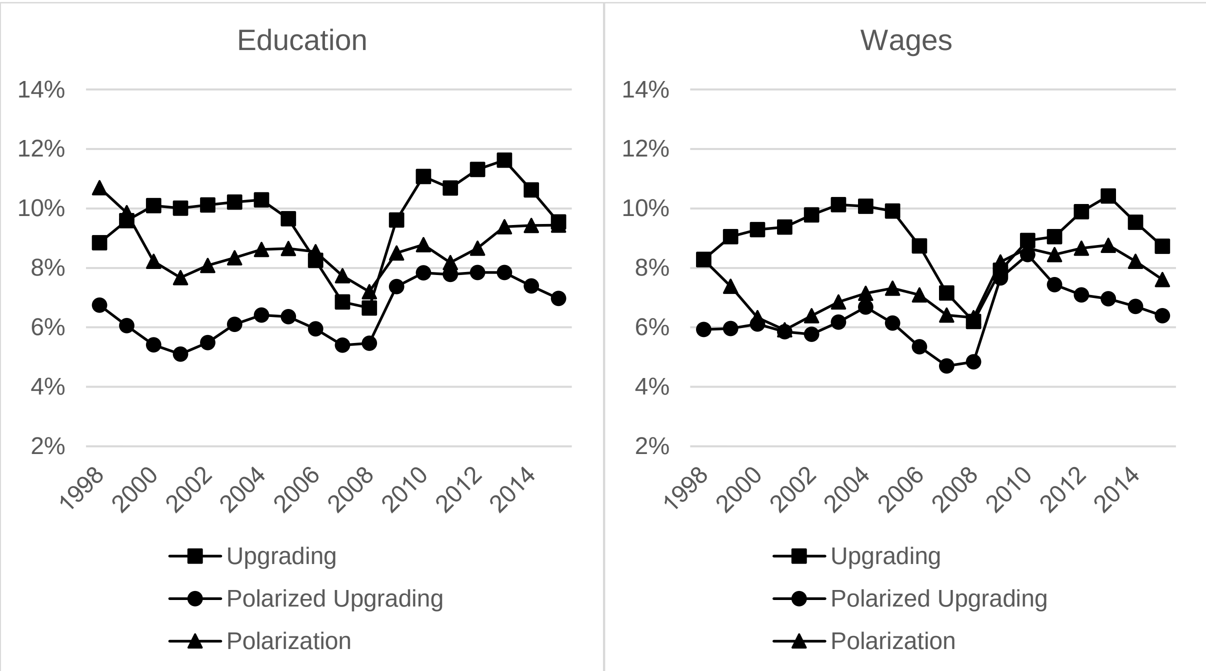
Unfortunately, empirical studies on this subject are not very numerous. To my knowledge, only two comparative studies have been conducted with a focus on the trade-off between polarization and unemployment. First, Hornstein et al. (2004) support the argument by providing positive evidence: They observe a strong increase in income inequality in the USA, while unemployment rates remain relatively constant. In Europe however, they generally find a considerable increase in unemployment, while income inequality remains rather constant. They explain this discrepancy by referring to institutional differences which allow for stronger growth of low wage occupations in the USA than in Europe. Thus, the USA seemed to accept higher inequality in exchange for lower unemployment, while Europe generally chose to accept higher unemployment.

Oesch (2013), on the other hand, argues against the trade-off hypothesis by referring to evidence from Denmark, Spain, Switzerland, Britain, and Germany. Even though he finds that unemployment of lowly educated workers increases in times of rapid occupational upgrading, he claims that the causality is reversed: Unemployment among lowly educated workers leads to upgrading, not the other way around. In recessions, lowly educated workers are fired in large numbers for various reasons and therefore being pushed out of the labor market. This has not much to do with automation or any of the effects mentioned previously, but by pushing lowly educated workers out of employment, the occupational structure inevitably displays stronger signs of upgrading.

Further, Oesch finds that overall unemployment rates did not increase significantly in any of the countries that he examined. On the contrary, he even shows evidence that upgrading is possible without increasing unemployment: In Denmark and Switzerland, strong growth among top quintiles and strong decline in bottom quintiles did not lead to increased unemployment among lowly educated workers. Apparently, lowly educated workers disappeared just as fast as occupations with low educational requirements in these two cases. Thus, Oesch concludes that the trade-off between polarization and unemployment is not a necessity, if educational systems are prepared to train and retrain people according to the situational requirements.

As these two contradictory conclusions demonstrate, there is no consensus about the relationship between polarization and unemployment. Therefore, I want to contribute to this debate by briefly testing the suggested effect with our data on occupational change. To do so, I use data on unemployment rates from the OECD, and calculate mean values for different groups of countries over time. The countries are divided into groups according to their pattern of occupational change, thus joining all polarizing, all upgrading, and all polarized upgrading countries together. Naturally, educational requirements and wages are treated separately in my analysis. The classification of countries can be reviewed in figures 3 and 5.

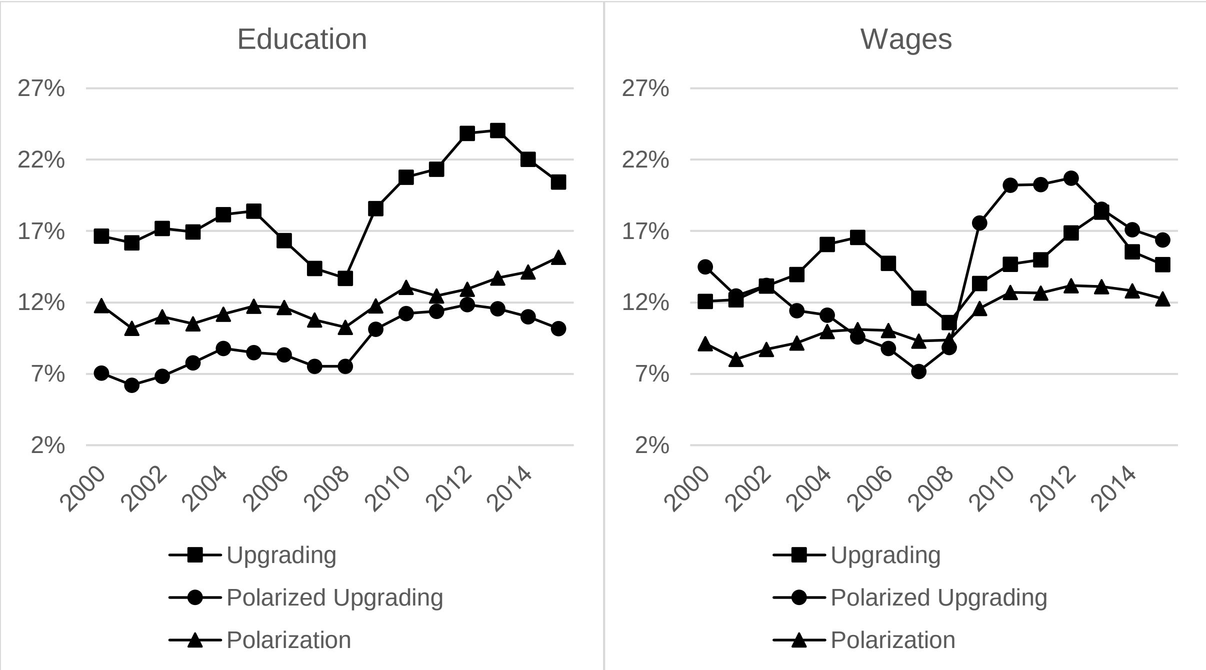
Figure 18: Unemployment Rates across Patterns of Occupational Change



As depicted in figure 18, countries that displayed a clear pattern of upgrading between 1998 and 2015 were also the countries with highest unemployment rates on average. This applies equally to countries upgrading in the educational or in the wage structure. This can be seen as support for the trade-off argument. However, it is interesting that countries displaying polarized patterns are not the ones with lowest unemployment. Rather, polarized upgrading seems to be the best option to keep unemployment low. Possibly, strong growth at the top of the occupational structure and slow decline of bottom-end occupations provide enough opportunities for finding alternative occupations instead of becoming unemployed.

Another interesting observation can be made by looking at the change of unemployment rates over time. Apparently, unemployment in upgrading countries is not expanding significantly more than in other countries. Rather, it remains at a relatively high level. Nevertheless, unemployment rates in upgrading countries clearly display the most extreme fluctuations. Thus, it seems like unemployment in upgrading countries is more depending on the economic cycle than in other countries. This could be interpreted as support for Oesch's argument, as described above: In countries, that are severely hit by recessions, large numbers of lowly educated people are fired. Therefore, these countries are more likely to display patterns of upgrading.

Figure 19: Unemployment Rates of Lowly Educated Workers across Patterns of Occupational Change



In addition to total unemployment rates, I also use a more specific approach by measuring only unemployment rates of lowly educated workers[15] across these six different groups. The results are displayed in figure 19. As we can see on the left side, the relations are the same as before, but the gap between unemployment of upgrading countries and other countries has become even bigger than before. Also, unemployment is increasing considerably faster in upgrading countries than in others in this chart. Thus, the trade-off effect seems to be most visible in unemployment of lowly educated workers, if upgrading is measured by educational

[15] Persons holding less than an upper secondary degree

requirements: If more jobs with low educational requirements disappear, more lowly educated workers become unemployed. This is not a surprise, since it is exactly what theory would predict.

However, even on the left side, countries with polarized upgrading are still displaying less unemployment than countries with increasing numbers of jobs in bottom quintiles. This has not been anticipated by the theory.

On the right side, finally, the trade-off effect seems to have disappeared completely. No clear patterns can be observed, since all groups display similarly high unemployment rates and even switch ranks several times. Thus, upgrading of the wage structure seems to have no effect on unemployment of lowly educated workers.

Together, these might be interesting findings which help to understand the effects of occupational change on unemployment. However, they are tentative at best. To properly examine the causal effects at work, one would certainly have to conduct more sophisticated analyses. For example, previous occupations of unemployed people could be examined to understand whether they were replaced by machines or whether they became unemployed due to other reasons. To my knowledge, studies of this kind are not published yet. Therefore, this would probably be a promising idea for future research.

Conclusion

In the current academic discourse, it is widely accepted that technological progress is the main driver of occupational change. Nevertheless, there seems to be no consensus on which occupations are actually affected by automation in Europe. Some authors claim that low-skilled occupations can be automated most easily and therefore they are bound to disappear first. Since high-skilled occupations are expanding at the same time, these authors predict an upgrading of the whole occupational structure. Other authors however argue that occupations in the middle of the skill spectrum are most affected by automation due to their higher routine task intensity. Therefore, these authors expect occupations in the middle of the skill spectrum to decline most quickly, while high-skilled occupations grow, and low-skilled occupations remain relatively stable. In consequence, they expect that technological progress would ultimately lead to a polarization of labor markets. Obviously, these two theoretical approaches directly contradict each other. One clearly needs empirical analyses to determine which of those two scenarios is more plausible. However, results of existing studies are widely inconclusive: Some authors find evidence in favor of upgrading labor markets, others find pervasive patterns of polarization. To explain this discrepancy in the existing literature was the goal of this Master's thesis.

In my own analyses of 23 European countries from 1998 until 2015, I find several issues that can explain the observed discrepancy. A first reason can be found in the categorization of patterns. In addition to clear patterns of upgrading or polarization, many countries display a pattern of occupational change that lies somewhere in between. In these countries, occupations in the middle of the occupational structure are declining most quickly, but those at the bottom are declining, nevertheless. Thus, they show characteristics of both upgrading and polarization at the same time. Clearly, this leaves room for interpretation. Until now, authors usually categorized these countries as either upgrading or polarizing, depending on their preferences. This way, they could come to different conclusions even when in fact they were looking at the same patterns. For this reason, I argue that we must define a proper term for this pattern and treat it as a separate category. Since it displays characteristics of both upgrading and polarization simultaneously, I propose the term "polarized upgrading".

Second, I show that the measurement of skills is a crucial factor in determining the patterns of occupational change: If skills are measured by educational requirements, labor markets display a distinct upgrading pattern on average. But if skills are measured by wages, labor markets tend more strongly towards polarization, thus resulting in a pattern of polarized upgrading on average. The reason for this can be found in the ranking of occupations. Apparently, some large occupational groups are systematically ranked higher in the wage structure than in educational structure and vice versa. This clearly shows that education and wages cannot be used interchangeably as proxies for skills. These two measurements obviously don't measure the same concept and must therefore be treated separately in all cases. However, many authors until now have simply been using one of the two proxies without much consideration and claimed that they both measure skills. This can explain why different authors have found different patterns of change: They simply did not examine the same kind of occupational structure.

Third, my analyses also display a wide variety of patterns across countries, even when examining the educational structure separately from the wage structure. Independently of the structure under scrutiny, some countries always show clear upgrading, some clear polarization, and some polarized upgrading. Even though countries tend more strongly towards upgrading in the educational structure, and more strongly towards polarized upgrading in the wage structure, there are always numerous countries which deviate from this average pattern. Some countries display polarized patterns of change in their educational structure, and some clear upgrading patterns in their wage structure. This can only mean that, apparently, occupational change does not cause uniform patterns of change across different labor markets. It is therefore impossible to generalize findings from only a small number of countries, since patterns in other countries might look completely different. However, most studies on the topic examine only a small number of countries and thus seem to contradict each other at first sight, when in fact they only find different patterns due to different country samples. The observed cross-country variance is therefore at least partly responsible for the lack of consensus, simply because no uniform pattern can be found across countries.

Together, these three issues can probably explain why there is no consensus on the patterns of occupational change in Europe to date. By considering these issues, it becomes possible to understand the existing empirical literature not as contradictory, but as complementary. Diverging results are therefore not necessarily caused by real disagreement over the empirical facts but are rather a consequence of the multifaceted nature of occupational change itself.

However, these findings have important implications for the theories on occupational change. First, it is clearly necessary for any valid theory to explain why occupations in the middle of the wage structure and at the bottom of the occupational structure are declining the most on average. But as I show by testing different variables, both dominant theories are unable to explain the observed patterns of occupational change on their own. All available variables, that measure how easily occupations can be automated, predict patterns which don't match our observed patterns. Thus, I conclude that technical feasibility cannot be the only relevant factor determining occupational change. In consequence, I conclude that the theoretical framework must be expanded in order to allow for other influences. I strongly suggest a framework which considers potential costs and benefits of automating occupations equally. I also propose several possible factors that can be included in such a broader framework. These are wage costs, productivity gains, consumer preferences and offshoring of jobs.

Second, the cross-country variance must also be considered by any valid theory. If certain occupations decline in one country, but grow in another, then clearly the inherent characteristics of these occupations cannot explain what is happening. Instead, we must look for potential causes in the country-specific circumstances. Again, I suggest several possible factors. For one, the original composition of labor markets is important: If nobody is working in agricultural occupations in a country, then nobody can be replaced by machines in these occupations. Further suggestions are based on the potential effects of income inequality, which allows for the creation of jobs with low wages, and of higher education, which is required for many growing occupations.

Even though I find preliminary support for some of these effects with simple descriptive models in this thesis, all of them certainly require more elaborate empirical analyses. First, it would be necessary to find ways how to operationalize all the proposed effects, and then one should estimate multivariate models in order to separate the effects from each other. Until then, these suggestions should be treated as what they are: First indications of potential effects, but nothing more. The same also applies to another topic, which I briefly outlined in the last chapter: Even though I find higher unemployment rates in upgrading countries than in polarizing countries, this should only be seen as a preliminary result. More sophisticated research is clearly needed concerning this matter.

Overall, this thesis can be seen as a refutation of technological determinism. It started with the assumption that technological progress determines the patterns of occupational change, since this is claimed by the dominant theories. In the course of this thesis however, it became clear that technical feasibility alone is unable to explain all the patterns of change that we observe in European countries. Therefore, I call for an expansion of the current theoretical framework and introduce several potential alternative effects. But still, we are far from having a complete explanation of occupational change based on empirical evidence. Some potential effects are not tested at all, and others only by using simple descriptive statistics. More complex models would be required to claim any real explanatory power. This clearly leaves room for future research. Nevertheless, it seems rather untenable now to assume that technology is the only determinant of occupational change. And whatever the other determinants might be, this means that we are not completely at the mercy of technology. Instead, it seems quite likely that we are able to shape occupational change according to our wishes at least to some extent. We just need to learn how this can be done.

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Appendix

Change in Employment Share of Major Occupational Groups (ISCO) on 23 European Labor Markets, 1998-2015*

Country	Managers	Professionals	Technicians and associate professionals	Clerical support workers	Service and sales workers	Skilled agricultural and fishery workers	Craft and related trades workers	Plant and machine operators and assemblers	Elementary occupations
AT	-1.59%	+3.23%	+7.23%	-1.85%	+0.81%	-1.39%	-4.22%	-3.60%	+1.40%
BE	+1.08%	+6.16%	-0.36%	-4.66%	+1.05%	-0.61%	-3.33%	-0.49%	+1.16%
CH	+1.91%	+4.52%	+2.56%	-4.55%	+0.63%	-1.27%	-2.17%	-0.85%	-0.79%
CZ	-0.55%	+2.59%	+5.26%	-0.63%	+0.34%	-1.11%	-4.01%	+1.82%	-3.72%
DE	-0.54%	+1.89%	+3.30%	-0.29%	+0.47%	-0.39%	-3.73%	-0.70%	+0.00%
DK	-2.45%	+5.60%	+5.96%	-3.06%	+1.95%	-0.83%	-3.26%	-2.08%	-1.82%
EE	+0.84%	+8.37%	-2.00%	+2.19%	+1.71%	-3.75%	-4.91%	+0.30%	-2.75%
ES	-0.86%	+3.47%	+3.93%	-0.37%	+4.81%	-3.02%	-5.11%	-2.22%	-0.63%
FI	-1.12%	+4.87%	+2.44%	-3.78%	+4.11%	-2.37%	-2.09%	-2.33%	+0.26%
FR	+0.86%	+4.07%	+1.49%	-3.69%	-0.77%	-0.48%	-1.96%	-1.68%	+2.16%
GR	-1.95%	+4.33%	+2.31%	+1.43%	+4.79%	-5.53%	-5.72%	-1.35%	+1.69%
HU	-0.41%	+3.13%	+0.53%	-0.06%	+1.60%	-1.28%	-5.93%	+0.48%	+1.94%
IE	-4.77%	+4.62%	+2.26%	-0.80%	+4.57%	+3.77%	-3.46%	-3.87%	-2.31%
IS	+1.17%	+10.82%	+2.81%	-2.92%	+1.83%	-4.46%	-5.59%	-1.53%	-2.13%
LU	-3.42%	+17.44%	+2.79%	-5.01%	-0.39%	-1.91%	-6.10%	-3.38%	-0.01%
NL	-2.56%	+5.69%	-0.67%	-1.03%	+1.95%	-1.02%	-2.95%	-1.49%	+2.07%
NO	-4.03%	+7.73%	+5.92%	-4.14%	+2.81%	-2.89%	-1.64%	-1.39%	-2.36%
PL	+0.80%	+8.42%	+1.47%	-0.95%	+1.34%	-7.35%	-3.92%	+1.02%	-0.83%
PT	-1.16%	+7.36%	+4.47%	-0.57%	+3.38%	-3.78%	-8.37%	-0.22%	-1.10%
SE	+0.58%	+6.27%	+2.91%	-2.39%	-0.43%	-0.52%	-3.65%	-3.15%	+0.38%
SI	+3.66%	+9.37%	+1.20%	-3.10%	+1.49%	-6.88%	-0.80%	-7.90%	+2.96%
SK	+0.42%	+2.02%	-0.02%	-0.63%	+4.70%	-1.05%	-5.92%	+2.75%	-2.28%
UK	+0.87%	-0.10%	+3.96%	-3.86%	+2.80%	+0.21%	-3.22%	-2.32%	+1.66%

*Due to the altered ISCO classifications after 2010, the changes 1998-2010 and 2011-2015 are first calculated separately and then added together.

Predicted and Observed Patterns of Occupational Change (P=Polarization; PU=Polarized Upgrading; U=Upgrading)

	Educational Structure					**Wage Structure**				
Country	Autor & Dorn	Fernández-Macías & Hurley	Marcolin et al.	Frey & Osborne	Observed 1998-2015	Autor & Dorn	Fernández-Macías & Hurley	Marcolin et al.	Frey & Osborne	Observed 1998-2015
AT	P	U	U	U	Other	P	U	U	U	PU
BE	P	U	U	U	P	P	U	U	PU	P
CH	P	U	U	U	PU	P	U	U	U	U
CZ	P	U	U	U	U	P	U	U	U	U
DE	P	U	U	U	PU	P	U	U	U	P
DK	P	U	U	U	PU	P	U	U	U	PU
EE	P	U	U	U	U	P	U	U	U	PU
ES	Other	U	U	U	U	P	U	U	U	Other
FI	P	U	U	PU	PU	P	U	PU	U	U
FR	P	U	U	U	P	P	PU	PU	U	P
GR	Other	U	U	U	U	-	-	-	-	-
HU	P	U	U	U	Other	Other	U	U	U	Other
IE*	Other	U	U	U	PU	Other	U	U	U	P*
IS	P	U	U	U	U	P	PU	U	U	P
LU	P	U	U	U	PU	P	U	U	PU	PU
NL	P	U	U	U	PU	Other	U	U	U	P
NO	P	U	U	U	U	Other	U	U	U	Other
PL	P	U	U	U	U	P	U	PU	U	U
PT**	P	U	U	U	U	P	-	PU	U	U
SE	P	U	U	U	U	P	U	U	U	PU
SI	P	U	U	PU	U	P	U	PU	PU	U
SK	P	U	U	PU	U	P	U	U	U	Other
UK	P	U	U	U	PU	P	PU	U	U	P

* only period 1998-2010 covered for wage structure in Ireland

** only period 2011-2015 covered for wage structure in Portugal

Original Employment Share of Major Occupational Groups (ISCO) on 23 European Labor Markets, 1998

Country	Managers	Professionals	Technicians and associate professionals	Clerical support workers	Service and sales workers	Skilled agricultural and fishery workers	Craft and related trades workers	Plant and machine operators and assemblers	Elementary occupations
AT	8.1%	10.0%	14.1%	14.1%	13.1%	5.9%	16.9%	8.8%	8.9%
BE	12.1%	19.0%	10.2%	15.8%	10.7%	2.3%	13.4%	8.0%	8.6%
CH	6.2%	14.9%	20.0%	14.5%	13.6%	4.8%	15.0%	4.8%	6.1%
CZ	6.9%	9.6%	18.1%	8.1%	12.5%	2.2%	21.3%	12.7%	8.6%
DE	6.5%	13.3%	20.2%	12.8%	11.5%	2.1%	18.3%	7.5%	7.6%
DK	7.2%	12.3%	18.2%	11.5%	16.2%	2.7%	11.9%	7.3%	12.7%
EE	14.4%	11.0%	13.3%	4.4%	11.1%	4.9%	16.9%	12.6%	11.3%
ES	9.0%	11.7%	9.0%	9.6%	13.7%	5.4%	17.1%	10.5%	14.1%
FI	8.9%	17.2%	16.4%	9.1%	12.1%	6.5%	12.3%	9.8%	7.7%
FR	9.3%	10.4%	17.2%	14.2%	12.3%	4.5%	13.4%	10.9%	7.8%
GR	12.2%	12.1%	6.9%	9.4%	12.2%	17.3%	16.0%	8.0%	5.9%
HU	7.1%	11.5%	13.1%	9.1%	13.3%	3.8%	22.3%	11.2%	8.6%
IE	18.8%	15.0%	5.4%	13.2%	14.2%	0.9%	13.1%	9.8%	9.6%
IS	8.5%	12.0%	13.4%	8.5%	19.0%	7.0%	16.2%	6.3%	9.2%
LU	5.9%	14.7%	19.4%	15.3%	9.4%	3.5%	12.9%	8.2%	10.6%
NL	12.5%	17.8%	18.0%	12.0%	12.9%	1.8%	10.9%	6.8%	7.3%
NO	11.6%	9.0%	19.5%	9.9%	19.4%	4.4%	11.1%	8.4%	6.6%
PL	6.5%	10.3%	11.5%	7.8%	10.0%	18.0%	19.1%	8.7%	8.2%
PT	8.0%	6.2%	7.6%	9.0%	13.2%	11.8%	22.9%	8.6%	12.7%
SE	5.3%	15.1%	20.2%	10.8%	17.7%	2.6%	12.0%	10.9%	5.2%
SI	5.5%	9.7%	12.9%	11.7%	11.9%	11.4%	11.4%	20.7%	4.8%
SK	5.8%	9.5%	16.6%	8.7%	11.9%	2.0%	21.1%	13.7%	10.6%
UK	15.4%	15.5%	8.5%	16.3%	14.8%	1.1%	12.1%	8.2%	8.1%

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Zürich, 11.12.2018

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